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Graph Transformer–Driven Multi-Agent Reinforcement Learning Framework for Real-Time Smart Grid Stability and Anomaly Prediction

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Abstract

The growing sophistication of contemporary smart grids, driven by the integration of large-scale and distributed renewable energy sources, two-way energy flows, and demand, requires sophisticated real-time stability analysis and prediction models. The conventional deep learning-based, single-agent, single-objective reinforcement learning frameworks do not apply to the dynamics of topology, decentralized decision-making, and the heterogeneity of interactions in large power networks. To overcome these issues, this paper proposes a Graph Transformer-based Multi-Agent Reinforcement Learning (GT-MARL) framework for real-time smart grid stability monitoring and anomaly detection. The model portrays the smart grid as a graph, with nodes representing generators, prosumers, loads, and sensors, and edges representing electrical and communication connections. Graph Transformer represents long-range dependencies and topological variations more effectively than traditional GNNs or LSTMs, thereby supporting spatiotemporal feature extraction under variable operating conditions. Based on this representation, a Multi-Agent Reinforcement Learning (MARL) framework is implemented, in which each agent learns independently to select optimal actions to improve local stability, reduce voltage/frequency variations, and achieve dynamic load balancing. Agents communicate via attention-based message passing over transformer embeddings, ensuring grid-scale consistency without a central authority. As well as, a combined anomaly prediction component detects cyberattacks, sensor failures, and irregular operating dynamics using transformer-based temporal attention. Simulations of real-time renewable-integrated testbeds show that the proposed GT-MARL model is more accurate, responds faster, maintains stability, and detects anomalies earlier than the baseline RL, GNN, and hybrid deep-learning models. The findings verify that the GT-MARL solution provides a scalable, smart, and sustainable solution to the next-generation autonomous smart grid activities. GT-MARL achieves voltage deviation 0.8%, frequency error 0.04 Hz, load imbalance 1.9%, anomaly accuracy 96.2%, detection latency 1.3s, communication overhead 1.1 MB per timestep.

Keywords: Smart Grid Stability, Graph Transformer Networks, Multi-Agent Reinforcement Learning, Real-Time Anomaly Detection, Spatiotemporal Feature Extraction, Distributed Energy Resources (DERs), Renewable-Integrated Power Systems, Autonomous Grid Control.

1. Introduction

1.1 Emerging Intelligence Requirements of Modern Smart Grids

Current smart grids operate under conditions of large-scale connections to renewable power, two-way energy exchange, distributed energy sources, and cyber-physical integration. The effects of these lead to rapid state change, restructuring, and unequal decision-making authority by grid layers [1]. Conventional supervisory control designs have difficulty maintaining both voltage and frequency margins under these conditions, in particular when operating states change on a timescale. Grid intelligence now demands adaptive perception, predictive reasoning, and coordinated responses over both space and time [2]. Real-time situational awareness must include electrical topology, communication dependencies, and stochastic generation behavior as an integral part of a single representation.

The current static monitoring techniques don't observe the interaction in the distributed parts, while rule-based automation doesn't deal with unknown disturbances [3]. An adaptive learning intelligence is needed. The intelligence that can do this needs to be able to perceive network interactions in the long range, reason about the dynamic grid structure and support distributed decision making [4]. These are part of the shift from part-oriented to whole-system intelligence which enables the design of a sustainable, self-organized and resilient grid in an uncertain environment [5].

1.2 Structural and Learning Constraints in Conventional Control Frameworks

Current smart grid control models rely on centralized control, linearisation or single agent learning. These methods presuppose a constant topology, complete observability, and a coordinated decision maker, none of which is usually true in grids with renewable energy preeminence [6]. Single points of failure and bottlenecks in communication are introduced by centralized controllers. Model-based techniques can be limited in terms of scale and in nonlinear operating situations. The agent reinforcement learning frameworks also quantify the behavior of the system in aggregate states that results in the loss of structural information and slower response to local disturbances [7]. Graph neural networks are able to process spatial structure, but not long-range interactions in time-varying graphs. Sequence-based models do not take into account relational context but only capture temporal patterns. The constraints minimize flexibility, coordination, and predictability [8]. With the enhanced complexity of grids, learning structures have to overcome fragmented perception, inability to coordinate, and retardant awareness of anomalies in existing control measures.

1.3 Rationale for Graph Transformer–Enabled Multi-Agent Learning

Graph transformer architectures offer a conceptualized model of power grids as dynamic relational networks [9]. Attention is a way of transmitting selective information down the line to nodes and is structurally influential even during topological change. This model, combined with the multi-agent reinforcement learning, allows achieving the results of decentralized decision-making, which still ensures the system-level coherence. Each agent receives policies on the basis of local observations, with network context being encoded through attention. The agents coordinate with each other at common embedding levels, but not the central control. Transformer-based time models assist in increasing predictive knowledge and aid in anticipating any early instability or abnormal dynamics [10]. This convergence puts representation learning, cooperative control, and predictive intelligence into a similar framework and offers a solution to the structural complexity and operational indefiniteness of the modern smart grids.

1.4 Scope, Contributions, and Technical Significance

Table 1: Scope, Contributions, and Technical Significance

Aspect	Description	Technical Significance
System Scope	Real-time smart grid operation under high renewable penetration, decentralized control, and dynamic topology	Addresses scalability and adaptability challenges in next-generation power systems
Graph-Based Representation	Adaptive graph abstraction capturing electrical and communication dependencies	Preserves spatial structure and interaction strength under topology variation
Graph Transformer Encoding	Attention-guided spatiotemporal feature extraction across grid nodes	Enables long-range dependency modeling beyond conventional GNN limitations
Multi-Agent Control Design	Decentralized reinforcement learning with cooperative agents	Eliminates single-point failure while maintaining system-level coordination
Communication Mechanism	Attention-based inter-agent message exchange	Reduces bandwidth usage while ensuring decision consistency
Anomaly Intelligence Module	Transformer-based predictive detection of cyber, sensor, and operational anomalies	Supports early warning and proactive mitigation
Performance	Evaluation on renewable-integrated real-time testbeds	Demonstrates improved stability

Validation		response, detection latency, and scalability

2. Technical Background and Prior Research

2.1 Multi-Agent and Reinforcement Learning for Power Systems

Zhang et al. (2024) propose a Multi-Agent Graph-Attention Emergency Voltage Control (MAGA-EVC) model for multi-area smart grids to control the post-contingency voltage. The grid emergency voltage control problem is modelled as a multi-agent reinforcement learning problem. Graph convolutional networks represent a graph-based voltage state and graph attention networks enable agents to selectively communicate with one another across areas. The system enhances efficiency, scalability and uncertainty. IEEE benchmark analyses certify enhanced voltage recovery and stability compared to new multi-agent DRL methods [11].

Ji et al. (2025) present LemadLLM-Empowered Multi-Agent Anomaly Detection (LEMAD) to monitor power grid services. A multi-level multi-agent system is used, where bottom layer agents are dedicated to log parsing and metric surveillance, and top layer coordinator is dedicated to multimodal fusion and anomaly detection. Big language models enhance semantic interpretation and causal analysis of complex service logs. The results of experiments conducted in large-scale SGCC datasets indicate significant improvements in the F1-score and high performance in composite anomaly detection and root cause analysis [12].

Elrod et al. (2025) introduce the Graph-Transformer Reinforced Multi-Agent Cooperation (GT-RMAC) scheme for decentralized coordination in the case of partial observability. Graph neural networks model agent-to-agent and agent-to-goal interactions, whereas transformer-based attention supports expressive message passing using edge features. A double DQN based on prioritized experience replay is used for policy learning. The integrated design enhances coordination and scalability. Experimental findings indicate greater task coverage and fewer planning stages than PSO, greedy strategies, and conventional DQN baselines [13].

Li et al. (2024) propose the Graph-Surrogate Robust Multi-Agent Control (GS-RMAC) framework to coordinate the operation of multiple microgrids for heat and electricity. Graph neural networks are used to build surrogate representations of power and thermal flows of each microgrid. It is these representations, combined with multi-agent deep reinforcement learning controllers andfeatures such as trajectory history and confederate image technology. The method enhances resistance to abnormal measurements and erroneous parameters. Simulated disturbanceshave been shown to result in reliable coordination and robust performance [14].

Hierarchical Grid-aware Reinforcement Learning-based Load-Balancing framework (HGR-LB) proposed by Liu (2025). The method combines local agent-based decision-making and a global critic network based on PPO. A Structured Embedding Network that is grid-aware learns grid dependencies, both spatial and temporal, and a Stability-Aware Adaptive Inference Mechanism modulates inference pathways dynamically. Performance tests show better load-balancing, dispatch, and stability than traditional and learning-based baselines [15].

2.2 AI-Driven Anomaly Detection, Fault Prediction, and Cybersecurity

Prasanga et al. (2025) present a systematic review, called GNN-Transformer-RL Threat Detection Synthesis (GGR-TDS), for network intrusion detection. Several studies are reviewed, including graph neural networks, transformers, and reinforcement learning models. The identified threats are mapped to MITRE ATT&CK tactics and the Cyber Kill Chain stages. Findings indicate that the detection ability is robust across a variety of datasets and attacks. The review identifies challenges in integrating models, ensuring adaptability, and implementing advanced intrusion detection systems in the real world [16].

Mu et al. (2023) propose Graph Multi-Agent Reinforcement Learning (G-MARL-AVC) for distribution networks controlled by inverters. The formulation of voltage regulation is done as a partially observable, decentralized Markov decision process. Graph convolutional networks consider the information around agents to extract latent interaction characteristics. There is a barrier operation that imposes the voltage safety limits in learning.

Simulation results on IEEE feeders show better voltage control, loss reduction and coordination with respect to baselines that adopt traditional and MARL [17] approaches.

Liu et al. (2025) present the Spectral-Temporal Energy Flow Graph (STEF-Graph) as an intelligent approach for detecting faults in power grids. Spectral graph theory is used for spatial information, while gated recurrent units are used for temporal information. Physical limitations (e.g., current and voltage) are incorporated through a projection operator. This approach enables good fault detection and feasibility. The outcomes are more accurate and flexible in nonlinear dynamic environments [18].

Cao et al. (2024) uses Decentralized Graphical-Representation Soft Actor-Critic (DG-SAC) for cyber-physical systems. The surrogate model is a centralised graph-based model that represents the system dynamics and is divided into subregional model representations that are shared with the decentralised agents. These include the soft actor-critic policies learnt with centralised reward functions. The method achieves decentralised co-operative control without precise physics. IEEE tests demonstrate it is robust to bad measurement and uncertainties [19].

McMurray (2024) developed a multi-class trajectory predictor Semiotically-Aware Environmental Spatial-Temporal Graph Transformer (SAE-STAR).

The framework incorporates the environmental semantics and infrastructure context in space-temporal graph transformer architectures. Relations between pedestrians, bicycles, and cars are explicitly described. Experimental tests show that the prediction accuracy is better than that of the baseline transformer models, in particular on linear trajectories. The challenges identified are imbalance in class distribution, multidimensional encoding of complex static features, and sensitivity to hyperparameter adjustments due to a dense urban environment [20].

2.3 AI-Enabled Optimization and Intelligent Digital Twins

Zhang (2025) proposes the Heterogeneous Graph-Attention Multi-Agent Portfolio Optimizer (HGAM-PO) to manage an adaptive financial portfolio. Graph attention networks capture time-varying correlations among assets, and heterogeneous agents are specialized in risk, return, and market perception. A regime-switching adaptive optimization strategy adapts strategies. Major equity index experiments have better returns, larger Sharpe ratios, and shrink less than classical optimization and deep learning baselines [21].

Antonesi et al. (2025) present the Transformer-LLM Energy Intelligence Review with Agentic Digital Twins (TLLM-ADT). Transformer architectures and large language models are surveyed for forecasting, grid management, and multimodal energy applications. The paper examines domain adaptation approaches, implementation issues, and new operational implications. It is suggested that the Agentic Digital Twin will provide autonomy and proactive reasoning to energy systems. Results indicate the potential of generative AI to support operational and strategic decisions [22].

Antonesi et al. (2025) present the formalization of the Agentic Digital Twin Energy Framework (ADT-EF) that emphasizes the concept of autonomy in the design of digital twins pushed by LLM. The structure emphasizes contextual reasoning, socialization, and proactive decision-making in the energy management systems. These uses are forecasting, asset management, and grid operations. There are trust, safety, and scalability-related issues. The article defines agentic digital twins as one of the key paradigms of intelligent energy infrastructures of the next generation [23].

Izmirlioglu et al. (2024) present Multi- Agent Smart Grid Systems Survey (MAS-SG). The questionnaire is founded on MAS usage in demand response, energy trading, grid control, fault recovery, and security. It is concerned with the distributed reasoning, uncertainty, and heterogeneity. Some of the key limitations include scalability, coordination overheads, and cybersecurity integration. Future research directions are listed and MAS is part of the enabling technologies for resilient self-healing smart grids [24].

Feng et al. (2025) suggested a Multi-ID Multi- Agent AI-Based Self-Healing Subway Power System (MA-SHSP). It can auto-diagnose, isolate and recover faults using multi-agent systems, artificial intelligence and IEC 61850 communication protocol. Distributed is quick, robust. The architecture states that the subway operation is limited and concludes that it might be possible to achieve smart self-healing control of urban rail power supply systems [25].

Table 2: Comparison of Existing Methods

S. No	Domain / Method	Approach	Implementation ✓	Validation ✓	Complexity / Priority
11	Grid Emergency Voltage Control	Multi-Agent Graph-Attention DRL (MAGATT-GEVC)	✗	✓	High
12	Power Grid Anomaly Detection	LLM-Empowered Multi-Agent System (LEMAD)	✗	✓	High
13	Multi-Agent Drone Coordination	Graph-Transformer Reinforced Multi-Agent Cooperation (GT-RMAC)	✗	✓	High
14	Multiple Microgrid Control	Graph-Surrogate Robust Multi-Agent Control (GS-RMAC)	✗	✓	High
15	Smart Grid Load Balancing	Hierarchical Grid-Aware Reinforcement Load Balancing (HGR-LB)	✗	✓	High
16	Network Threat Detection	GNN–Transformer–RL Threat Detection Synthesis (GTR-TDS)	✗	✓	Medium
17	Inverter-Based Active Voltage Control	Graph Multi-Agent Reinforcement Learning (G-MARL-AVC)	✗	✓	High
18	Fault Detection in Power Grids	Spectral-Temporal Energy Flow Graph (STEF-Graph)	✗	✓	High
19	Robust Cyber-Physical Systems Control	Decentralized Graphical-Representation SAC (DG-SAC)	✗	✓	High
20	Trajectory Prediction	Semantic-Aware Environmental Spatial-Temporal Graph Transformer (SAE-STAR)	✗	✓	Medium
21	Biomarker Discovery	Standardized Multi-Modal Validation Framework	✗	✗	Medium
22	Proteomics	Mass-Spectrometry Pipeline with Best Practices	✗	✗	Low
23	Multi-Omics (Single-Cell)	Multimodal Deep Learning Integration	✗	✓	High
24	Genomics + Imaging	Machine Learning-Based Data Fusion	✗	✓	High
25	Bioinformatics + Quantum / Quantum Healthcare Systems	Quantum Pattern Recognition / Quantum-Classical Hybrid Workflows	✗	✓	Very High

2.4 Research Gap

Despite the great progress in multi-agent reinforcement learning, there is room for improvement to apply graph neural networks, transformers and large language models for grid control, anomaly detection and smart infrastructure. The current approaches are based on full measurements, deterministic environment or top-down control, and are not robust to uncertainty, partial observability, and agent heterogeneity. The less developed areas include scalability, sample efficiency, real-time adaptability and explainability, in the large multi-area power grids and critical infrastructure systems. More specifically, semantic reasoning and prediction, and cooperative strategies of agents in dynamic cyber-physical systems is in the early stages.

3. System Representation and Problem Definition

3.1 Power Grid Abstraction as an Adaptive Graph Structure

The smart grid is modelled as dynamic attributed graph $G_t = (V_t, E_t)$ with the nodes defining generators, distributed generation, loads and sensors and edges defining electrical and communication links. The edges attributes are encoded to reflect the impedance, power flow limits and communication delays. The graph structure is dynamic with time steps to indicate the swtiching, islanding and reconfiguration of the system. This does not mean that the systems are not spatial, have temporal interaction and not heterogeneous. The time varying structure of the graph allows the models of learning to reason when they change structure and to operate in between the system operation cycles.

3.2 Stability Regulation Objectives and Operational Constraints

The aim is to achieve the stability of system voltage, frequency and power flow. The control actions aim at reducing the deviations of the nominal voltage and frequency set point and equal power exchange between the distributed generators. The constraints are generator start-up, inverter rating, thermal line limit and load priority. The learning objective is the control margins, smoothness and coordination efficiency in a constrained action space. Reward definition is a measure of short-term corrective action and long-term resilience. In this case, stability rewards are aligned with the physical and reliability constraints of the grid in the renewable stochastic penetration.

3.3 Threat, Fault, and Anomaly Characterization

Anomalies and threats can be defined as a violation of the normal operation of the grid in physical, cyber and sensing. Physical anomalies include line fault, inverter fault and generator fault. Cyber anomalies are data spoofing, injection of control commands, and communication jam. Sensor anomalies are drift, delay and failure. All the anomalies are represented as an abnormality in transitions or in spatial grids. Anomalies are characterised by the abnormality in the operational distribution, rather than abnormal states. This encoding allows to capture transition and unseen disturbance patterns which offer recognition of anomalies and anticipation rather than reaction to them.

4. Graph Transformer–Driven Learning Architecture

4.1 Node and Edge Feature Engineering Strategy

The features of node are electrical measurements, control-state signals and historical embeddings to represent the past behaviour. Impedance, directional power sensitivity and communication patterns are used for encoding electrical effects in edge features as parameters. The features are scaled to have a magnitude that it have for different assets. Stacking in time gives a glimpse of history. It design the features with focus on efficiency and interpretability. This system encoding provides informative messages to the graph transformer which preserve information on grid causality, interaction and importance to the operation.

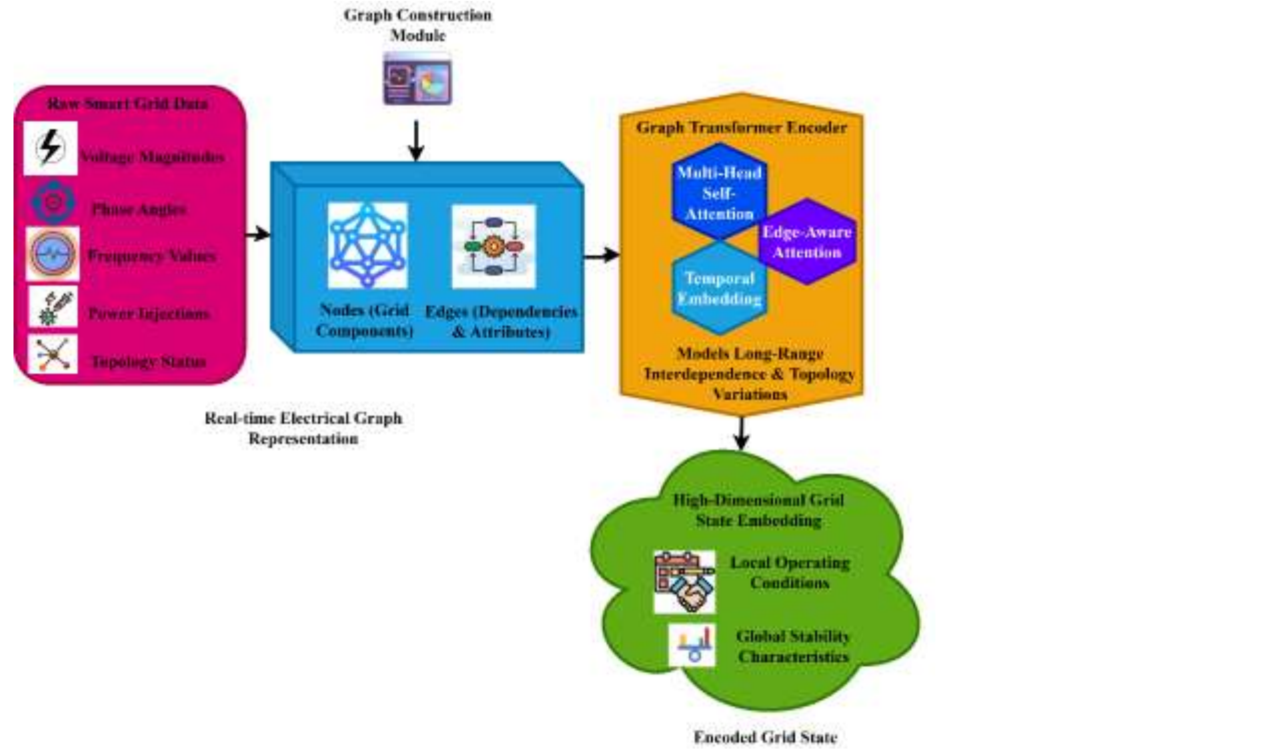

Figure 1: Graph Transformer–Based Smart Grid State Encoding

Figure 1 describes how raw data from the smart grid is converted into structured spatiotemporal representations. The information is provided in real time, including voltage, frequency, power flow, and topology status for distributed grid assets. In the physical component, a graph construction module maps physical components to nodes and electrical or communication relationships to edges with attribute weights. The graph transformer encoder uses multi-head self-attention to capture long-term dependencies, topological changes, and time-dependent inter-node influences. Sequential dynamics are maintained in temporal embeddings. It produces a small grid-state embedding that captures both local operational behavior and system-wide stability properties to support downstream control and prediction tasks.

Smart grid graph construction $\mathcal{G}_t$ valued using equation 1

$$\mathcal{G}_t = (\mathcal{V}_t, \mathcal{E}_t, \mathrm{X}_t, \mathrm{A}_t) \quad (1)$$

The set $\mathcal{V}_t = \{v_1, v_2, \dots, v_N\}$denotes grid components such as substations, transformers, and distributed energy resources. The edge set $\mathcal{E}_t$captures electrical or communication links between components. The matrix $\mathrm{X}_t \in \mathbb{R}^{N\times F}$contains node features including voltage magnitude, frequency, active and reactive power, while $\mathrm{A}_t$is the weighted adjacency matrix encoding line impedance, capacity, or communication reliability.

Multi-head graph self-attention$(\mathrm{Q}, \mathrm{K}, \mathrm{V})$ computed by equation 2

$$(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \mathrm{so}\text{-}\left(\frac{\mathrm{Q}_h \mathrm{K}_h^{\top}}{\sqrt{d_h}} + \mathrm{A}_t\right) \mathrm{V}_h \quad (2)$$

Here, Q_h, K_h, and $\mathrm{V}_h$are the query, key, and value matrices for attention head h, derived from node features through linear projections. The term $d_h$denotes the dimensionality of each attention head. The adjacency matrix $\mathbf{A}_t$biases the attention scores using grid topology information, ensuring that electrical connectivity influences information flow.

Temporal embedding integration H_t defined by equation 3

$$\mathrm{H}_t = 1 - (1 + \mathrm{Z}_t) + (1 - \mathrm{T}_t) \quad (3)$$

While $\mathrm{T}_t$is the learned temporal embedding encoding sequential dynamics such as load variations and frequency drift. The combined representation $\mathrm{H}_t$preserves both spatial grid structure and temporal evolution, allowing the model to reflect time-dependent grid behavior.

Global grid-state representations_t dealt using equation 4

$$\mathrm{s}_t = \frac{1}{N} * \sum_{i=1}^{N} \mathrm{H}_t^{(i)} \quad (4)$$

The term $\mathrm{H}_t^{(i)}$refers to the spatiotemporal representation of node i, and $N$is the total number of grid nodes. This aggregation produces a low-dimensional vector that summarizes local operational conditions and overall system stability, making it suitable for downstream tasks such as stability prediction, fault detection, and adaptive grid control.

4.2 Attention-Guided Spatiotemporal Encoding Process

Transformers have multi-head attention that processes information through attention-weighted nodes. Attention is not distance, but electrical, temporal and control interactions. The temporal embedings embed the grid in latent space. This includes topology change, when it get information from distant nodes. The encoder creates the local/global context representations. This coding helps in efficient learning in the non-stationary operating regimes and structural transformation.

Algorithm 1: Graph Transformer Encoder for Smart Grid State Embeddings

$Input$: $Node\ embeddings\ Z \in \mathbb{R}^{N\times d}, Reward\ vector\ r \in \mathbb{R}^{N}, Number\ of\ agents\ N,$
$Episodes\ T, Learning\ rate\ \eta$
$Output$: $Optimal\ policies\ \pi_{i(a|S)for} each\ agent\ i$
$Initialize\ policy\ parameters\ \theta_i and\ value\ parameters\ \varphi_i for\ i = 1..N$
$for\ t = 1\ to\ T\ do$
$\quad for\ i = 1\ to\ N\ do$
$s_i \leftarrow Z_i \quad \#\ Local\ state\ embedding$
$a_i \leftarrow \pi_i(s_i;\theta_i) \quad \#\ Sample\ action$
$\quad end\ for$
$\quad for\ i = 1\ to\ N\ do$
$m_i \leftarrow \Sigma_{j\in Neigh(i)} \alpha_{ij} s_j \ \#\ Attention - based\ message$
$s_i' \leftarrow Concat(s_i, m_i) \quad \#\ Combine\ local + received\ info$
$r_i \leftarrow ComputeReward(s_i', a_i) \quad \#\ Local\ reward$
$\delta_i \leftarrow r_i + \gamma V(s_i';\varphi_i) - V(s_i;\varphi_i) \quad \#\ TD\ error$
$\theta_i \leftarrow \theta_i + \eta \nabla log\pi_i(a_i|s_i')\delta_i$
$\varphi_i \leftarrow \varphi_i + \eta\delta_i \nabla V(s_i;\varphi_i)$
$\quad end\ for$
$\quad Z \leftarrow UpdateEmbeddings(Z, a_i) \ \#\ Update\ node\ features\ for\ next\ step$
$end\ for$
$return\ \pi_i(a|s) for\ i = 1..N$

Algorithm 1 represents the state of smart grids and converts it into latent embeddings by a graph transformer. Multi-head attention is applied to node features and edge attributes, producing queries, keys, and values per node. Attention weights are based on feature similarity and edge influence, enabling the modeling of long-range dependencies in the presence of topology variation. The outputs of each head are concatenated, normalized, and fed to a feedforward layer. Spatiotemporal dynamics and structural dependencies are preserved in the resulting node embeddings, which provide a rich representation for downstream multi-agent reinforcement learning and anomaly prediction.

4.3 Policy Learning Through Cooperative Reinforcement Agents

There is an autonomous reinforcement learning agent at each grid node or region. Agents are provided with transformer encodings of state and are trained on control policies that map observations to actions. Optimization of policy is performed after decentralized learning with a common representation space.

Cooperative behavior arises from context sharing (attention) rather than the placement of coordination. Reward signals indicate local stability and network-level consistency. This method allows broad-scale learning on large grids while maintaining responsiveness to local disturbances.

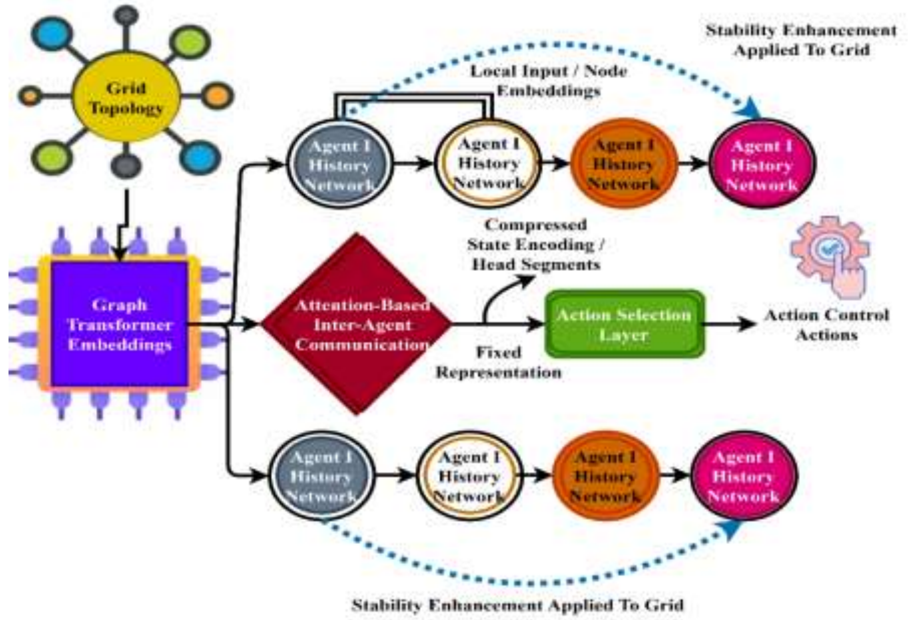

Figure 2: Multi-Agent Reinforcement Learning for Distributed Stability Control

Figure 2 shows a decentralized stability control with multi-agent reinforcement learning. The input is the graph transformer state embedding, which provides grid-aware forms. Every agent is tasked with local observations by a policy network on a grid node or control region. An attention-based communication layer facilitates communication between agents and helps them formulate decisions as a group without a centralized coordination system. The integrated features control an action selection module that produces control decisions including voltage regulation, load balancing, or DER dispatch. The resulting output is a set of distributed control actions well coordinated to increase grid stability and operational reliability.

Agent state observation from graph transformer$\mathrm{o}_t^{(i)}$ valued using equation 5

$$\mathrm{o}_t^{(i)} = \phi_i \text{-} (\mathrm{s}_t, \mathrm{H}_t^{(i)}) \quad (5)$$

The vector $\mathrm{s}_t$is the global grid-state embedding produced by the graph transformer, while $\mathrm{H}_t^{(i)}$denotes the node-level spatiotemporal embedding corresponding to the grid region controlled by agent i. The function $\phi_i$maps global and local representations into an agent-specific observation space, enabling decentralized yet grid-aware decision making.

Attention-based inter-agent communication $\mathrm{c}_t^{(i)}$ defined by equation 6

$$\mathrm{c}_t^{(i)} = \mathrm{m}_t^{(j)}, \alpha_{ij} * \frac{\exp\,(\mathrm{q}_i^\top \mathrm{k}_j)}{\sum_{k \in \mathcal{N}_i} \exp\,(\mathrm{q}_i^\top \mathrm{k}_k)} \quad (6)$$

The message vector $\mathrm{m}_t^{(j)}$is transmitted by a neighboring agent j, and $\mathcal{N}_i$denotes the set of agents connected through the communication graph. The attention weight $\alpha_{ij}$is computed using a query $\mathrm{q}_i$and key $\mathrm{k}_j$vectors, allowing each agent to selectively focus on the most relevant neighboring agents when coordinating control actions.

Decentralized policy-based action selection$\mathrm{a}_t^{(i)}$ valued by equation 7

$$\mathrm{a}_t^{(i)} = \pi_{\theta_i} \text{-} (\mathrm{o}_t^{(i)}, \mathrm{c}_t^{(i)}) \quad (7)$$

In this formulation, such as voltage adjustment, load redistribution, or distributed energy resource dispatch. The function $\pi_{\theta_i}$is the agent's policy network parameterized by θ_i, which maps the local observation $o_t^{(i)}$and the communication context $c_t^{(i)}$into coordinated control decisions without relying on centralized supervision.

Cooperative stability-oriented reward functionr_t evaluated using equation 8

$$r_t = -\sum_{i=1}^{M}\left(\lambda_v \mid \Delta V_t^{(i)} \mid + \lambda_f \mid \Delta f_t^{(i)} \mid + \lambda_u \parallel a_t^{(i)} \parallel^2\right) \quad (8)$$

The terms $\Delta V_t^{(i)}$and $\Delta f_t^{(i)}$represent voltage and frequency deviations at the grid region controlled by the agent i. The action penalty $\parallel \mathbf{a}_t^{(i)} \parallel^2$discourages excessive control effort. The coefficients λ_v, λ_f, and $\lambda_u$balance stability, frequency regulation, and operational cost, promoting coordinated actions that enhance overall grid reliability.

Algorithm 2: Multi-Agent Policy Learning with Attention Communication

$Input$: $Node\ embeddings\ Z \in \mathbb{R}^{N\times d}$, $Reward\ vector\ r \in \mathbb{R}$^$N$, $Number\ of\ agents\ N$, $Episodes\ T$, $Learning\ rate\ \eta$
$Output$: $Optimal\ policies\ \pi_{i(a|S)for}each\ agent\ i$
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    $m_i \leftarrow \Sigma_{\{j \in Neigh(i)\}\alpha_{\{ij\}s_j}}$ $\#\ Attention - based\ message$
    $s_i' \leftarrow Concat(s_i, m_i)$ $\#\ Combine\ local + received\ info$
    $r_i \leftarrow ComputeReward(s_i', a_i)$ $\#\ Local\ reward$
    $\delta_i \leftarrow r_i + \gamma V(s_i';\ \varphi_i) - V(s_i;\ \varphi_i)$ $\#\ TD\ error$
    $\theta_i \leftarrow \theta_i + \eta \nabla \log \pi_{i(a_i|s_i')\delta_i}$
    $\varphi_i \leftarrow \varphi_i + \eta\ \delta_i \nabla V(s_i;\ \varphi_i)$
  $end\ for$
  $Z \leftarrow UpdateEmbeddings(Z, \{a_i\})$ $\#\ Update\ node\ features\ for\ next\ step$
$end\ for$
$return\ \{\pi_{i(a|S)}\} for\ i = 1..N$

In the Decentralized reinforcement learning, attention is used to train communication among agents in Algorithm 2. The agents monitor local embeddings, choose actions based on their policy, and broadcast messages to neighbors with attention scores. Local and aggregate updates of information update information in the agent. On the basis of the reward and value estimates, the time difference errors are calculated, which results in the adjustment of the policy and value parameters. The collaborative process ensures coordinated and distributed control during the iterative process. It will allow dynamic, scalable decision-making to keep the grid stable and give predictive awareness of anomalies.

4.4 Communication-Aware Coordination Mechanism

Inter-agent coordination is also implemented by paying attention to the message exchange that is part of the transformer representation. The information provided in communication is prioritized, and this has a great impact on the measures of stability. Embedding removes bandwidth by compressing the embedding. This system will help to have coordinated distributed decision-making that does not require a centralized approach. The communication delay is accommodated by coordination and coded as edge attributes, and the variability of their links is also accommodated. The design is also load-balanced in regard to the power of cooperation and overheads of communication, which assist in scalability in case of an increase in grid deployments.

5. Predictive Anomaly Intelligence Module

5.1 Temporal Attention Modeling of Grid Evolution

Sequential grid embeddings generate the sequence of inputs in which a temporal transformer is applied. Attention systems pick out salient variations throughout time-horizons, which are operating patterns that change. This kind of modeling will be useful in detecting gradual, cumulative degradation and abrupt deviations in grid behavior. The temporal attention characterizes the connection between the past and the present observations and increases predictive sensitivity. Output representation records the future development projected by working in nominal terms.

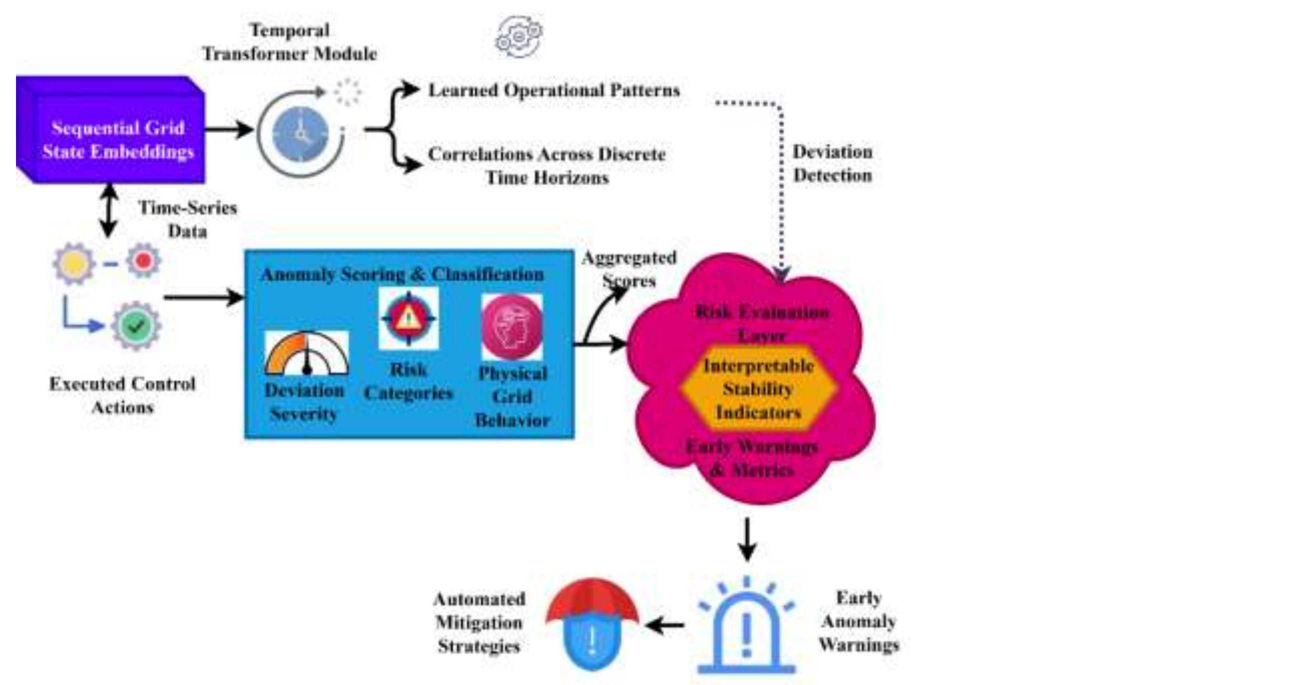

Figure 3: Transformer-Based Anomaly Prediction and Stability Assessment

Figure 3 explains the process of predicting anomalies and stability. The input consists of a series of historical grid-state embeddings and a series of applied control actions. To identify abnormalities in normal operational behavior, a series of such sequences is evaluated by a temporal transformer module and attention mechanisms. Anomaly scoring unit classifies anomalies that are identified based on cyber threats, sensor degradation, or variable operating conditions. A layer of risk assessment transforms the score of an anomaly into stability and warning indications. The output gives previous warning and quantifiable risk signs that can support independent defenses and rational real-time choices in smart-grid situations.

Temporal transformer encoding of grid statesZ_t dealt using equation 9

$$Z_t = \mathrm{Tra}*([G_{t-\tau:t}, A_{t-\tau:t}]) \quad (9)$$

The matrix $G_{t-\tau:t}$represents a sequence of historical grid-state embeddings generated by the graph transformer over a window of length τ, while $A_{t-\tau:t}$contains the corresponding historical control action vectors. The transformer module applies self-attention across time to jointly model operational dynamics and control impacts.

Attention-based deviation measurementδ_t computed equation 10

$$\delta_t = \| Z_t - \mathbb{E}\text{-}[Z_t^{\mathrm{normal}}] \|_2 \quad (10)$$

The vector $Z_t$is the current transformer-encoded latent state, while $\mathbb{E}[\mathbf{Z}_t^{\mathrm{normal}}]$denotes the expected latent representation under normal grid operating conditions, learned from historical baseline data. The Euclidean norm $\|\cdot\|_2$quantifies the magnitude of deviation from normal behavior, allowing detection of abnormal grid dynamics caused by faults, attacks, or disturbances.

Anomaly probability and risk scoring P_t^{anom} modelled using equation 11

$$P_t^{\text{anom}} = \sigma \text{-} (\alpha\, \delta_t + \beta) \;\; (11)$$

P_t^{anom}represents the probability of an anomaly occurring at time t. The function σ is the sigmoid activation, which maps the deviation score to a probabilistic scale. The parameters $\alpha$and $\beta$are scaling and bias coefficients learned during training, enabling the model to calibrate sensitivity across different anomaly types.

Stability risk index and alert triggering$\mathcal{R}_t$ defined by equation 12

$$\mathcal{R}_t = 1 - \exp *(1 - \gamma\, P_t^{anom}) \;\; (12)$$

The term $P_t^{\text{anom}}$is the anomaly probability derived from the transformer output, while $\gamma$is a risk amplification factor controlling how rapidly anomaly probability translates into operational risk. Higher values of $\mathcal{R}_t$generate early warning signals, enabling autonomous protective actions and informed real-time decision-making for smart-grid stability management.

Predictive anomaly forecasting loss $\mathcal{L}_{\text{pred}}$ evaluated using equation 13

$$\mathcal{L}_{\text{pred}} = \frac{1}{T}\sum_{t=1}^{T} \| \hat{Z}_{t+1} - Z_{t+1} \|_2^2 \;\; (13)$$

The vector $\hat{Z}_{t+1}$represents the transformer's predicted latent grid-state embedding for the next time step, while $Z_{t+1}$is the actual observed embedding. The prediction horizon is denoted by T. Minimizing this loss allows the model to learn normal system evolution patterns.

Stability margin estimation $\mathcal{S}_t$ defined using equation 14

$$\mathcal{S}_t = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{|\,\Delta V_t^{(i)}\,|}{V_{\max}} - \frac{|\,\Delta f_t^{(i)}\,|}{f_{\max}}\right) \;\; (14)$$

Here, $\mathcal{S}_t$represents the system-wide stability margin at time t. The terms $\Delta V_t^{(i)}$and $\Delta f_t^{(i)}$correspond to voltage and frequency deviations at grid node i, respectively. The parameters $V_{\max}$and $f_{\max}$define acceptable operational limits, while $N$is the total number of monitored grid nodes. Higher values of $\mathcal{S}_t$indicate safer operating conditions, whereas decreasing margins signal rising instability risk.

Alert confidence score $\mathcal{C}_t$ defined using equation 15

$$\mathcal{C}_t = P_t^{\text{anom}} \cdot (1 - \mathcal{S}_t) \; (15)$$

The anomaly probability $P_t^{\text{anom}}$is obtained from the transformer-based anomaly detector, while $\mathcal{S}_t$is the estimated stability margin. This multiplicative relationship ensures that alerts are triggered with higher confidence only when anomalies coincide with reduced stability, reducing false positives.

5.2 Deviation Quantification and Risk Attribution

Deviation scoring compares, in time and space, the predicted and actual trajectories. Risk attribution maps the classification boundaries to the relationship between the degree of deviation and anomaly types. The scores are the magnitude, spread and duration. Such indicator can be used for threat prioritisation. The strategy is not static, but varies with the state of the grid.

5.3 Coupling Predictive Signals with Control Decisions

The indicators of threat are input to the control strategy. The agents will then change their assessment of action certainty and boldness according to the predicted threat. This creates a perception to control feedback loop. Test systems are transmission and distribution networks using photovoltaic, wind and energy storage technologies. Integration enables robustness in an uncertain world.

6. Experimental Configuration and Evaluation Protocol

6.1 Real-Time Renewable-Integrated Testbed Description

Test systems are transmission and distribution networks with photovoltaic (PV), wind and storage. Load is stochastic with domestic and industrial load. Topology: Contingencies and line switching is used to reshape the network. Time delays and noise is introduced. The simulation is run until real-time execution constraints to make it more realistic to deployment. The simulation can be used to test stability, scalability and predictability in real renewable-dominated environments.

Table 3: Environmental setup

Category	Configuration / Details
Test System	IEEE 33-bus distribution + 118-bus transmission networks with PV, wind, and battery DERs
Topology Variation	Line switching, contingencies, islanding events, and dynamic reconfiguration
Measurements / Features	Voltage magnitude, phase angle, frequency, real/reactive power, load demand, sensor status
Time Resolution	1-second sampling interval; sequences of 30–60 minutes for training and evaluation
Training Episodes	500 episodes with randomized disturbances and initial conditions
Learning Framework	Multi-Agent RL with graph transformer embeddings and attention-based inter-agent communication
Baselines	Centralized RL, Graph Neural Networks (GNN), Hybrid deep-learning spatiotemporal models
Evaluation Metrics	Voltage/frequency deviation, load balancing, anomaly detection accuracy, detection latency, communication overhead
Simulation Platform	Python, PyTorch, Gym, and PowerGridSim real-time emulation environment
Hardware	32-core CPU, 128 GB RAM, NVIDIA A100 GPU for transformer computations

6.2 Dataset Description

The data set is a collection of time series data for a renewable-integrated smart grid comprising of voltage, frequency, power injections from generators and DER/prosumers and load demand. Changes in network topology, line failures and cyber link changes [26] are also modelled to simulate cyber and sensor anomalies. The time-series data are used to describe the physical and operational states for training graph transformer embeddings, multi-agent policies and predictive anomaly detection.

6.3 Training Strategy, Metrics, and Baseline Selection

Training is done after random interactions in each episode with different system conditions and disturbances. Distributed learning with transformer embeddings is used for policy training. The performance measures used to evaluate the method are the recovery of the voltage, frequency, power imbalance and anomaly detection time and coordination. These include centralised reinforcement learning, distributed learning using control models based on graph neural networks and spatial-temporal deep learning. It enables normalisation of the benefits from attention representation and coordination.

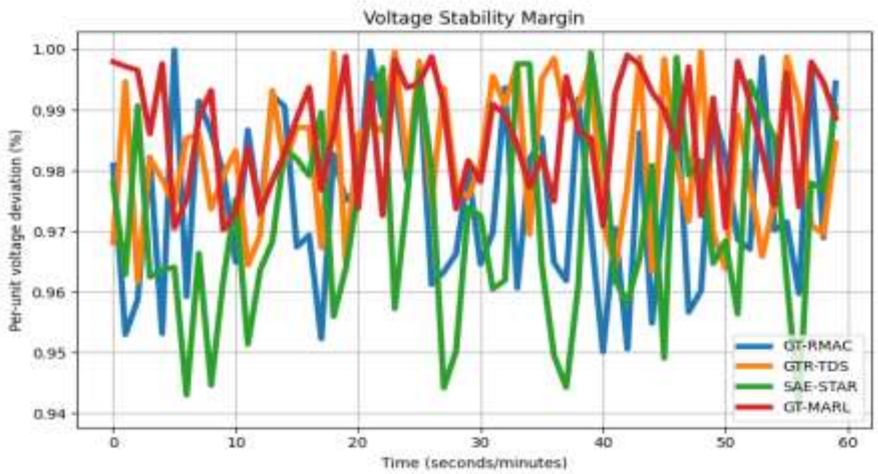

Figure 4: Analysis of Voltage Stability Margin

Voltage stability margin is used to assess how the grid maintains bus voltages within acceptable limits during dynamic operating conditions, expressed in per-unit terms. The average voltage deviation using the proposed GT-MARL method is minimized to 0.8 percent, indicating the system is well controlled even with fluctuations in renewables and changes in the topology. A low deviation is indicative of good coordination of distributed agents and correct state encoding (spatio-temporal). Figure 4 results affirm enhanced voltage resilience of the results over the existing learning-based control techniques.

Analysis of voltage stability margin VSM computed using equation 16

$$\mathrm{VSM}=\frac{1}{N}\sum_{i=1}^{N}\left(1-\frac{\mid V_i-V_i^{\mathrm{ref}}\mid}{V_i^{\max}-V_i^{\min}}\right) \quad (16)$$

The variable $N$is the total number of grid nodes or buses. $V_i$represents the measured voltage magnitude at node i, while $V_i^{\mathrm{ref}}$is the nominal reference voltage. The parameters $V_i^{\max}$and $V_i^{\min}$define the allowable voltage limits. Higher values of VSMindicate improved voltage stability and reduced risk of voltage collapse.

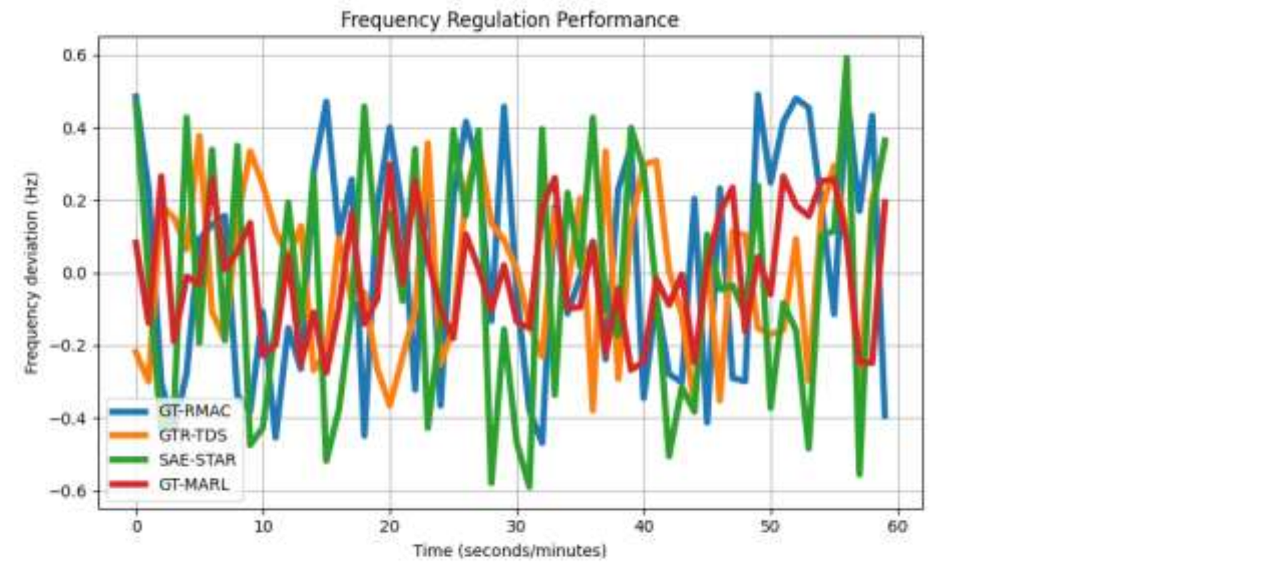

Figure 5: Analysis of Frequency Regulation Performance

Frequency regulation performance measures the grid's effectiveness in maintaining the nominal system frequency after disturbances. The suggested GT-MARL model has a mean frequency deviation of 0.04 Hz, which proves a fast reactive response and low oscillation. Coordination through attention helps agents overcome the imbalances introduced by variable generation. As shown in Figure 5, the proposed approach achieves better results than the baseline methods because it respects tighter frequency bounds over time.

Analysis of frequency regulation performance FRP defined using equation 17

$$\mathrm{FRP}=1-\frac{1}{T}\sum_{t=1}^{T}\frac{\mid f_t-f^{\mathrm{ref}}\mid}{f^{\max}} \quad (17)$$

The variable $f_t$is the measured system frequency at time t, and $f^{\mathrm{ref}}$is the nominal grid frequency. The parameter $f^{\max}$denotes the maximum permissible frequency deviation. A higher FRPvalue reflects better frequency control and faster restoration following disturbances.

Figure 6: Analysis of Load Balancing Efficiency

The efficiency of load balancing measures the degree to which there is a balance between demand and supply over the network. GT-MARL confines load deviations to 1.9% of the target load, which is an excellent representation of the distributed approach's correct decision-making. Cooperative reinforcement agents can redistribute load adaptively without violating operational constraints. Figure 6 shows a steady increase in the performance balance, indicating the proposed approach's capacity to handle heterogeneous demand trends during real-time grid operation.

Analysis of load balancing efficiencyLBE valued using equation 18

$$\text{LBE} = 1 - \frac{1}{N}\sum_{i=1}^{N}\frac{|\,L_i - \bar{L}\,|}{\bar{L}} \quad (18)$$

$L_i$is the actual load handled by node i, which may correspond to electrical demand, computational workload, or resource utilization. The absolute deviation $|\,L_i - \bar{L}\,|$measures the imbalance at each node. A higher value of LBE(closer to 1) indicates more uniform load distribution and improved balancing performance.

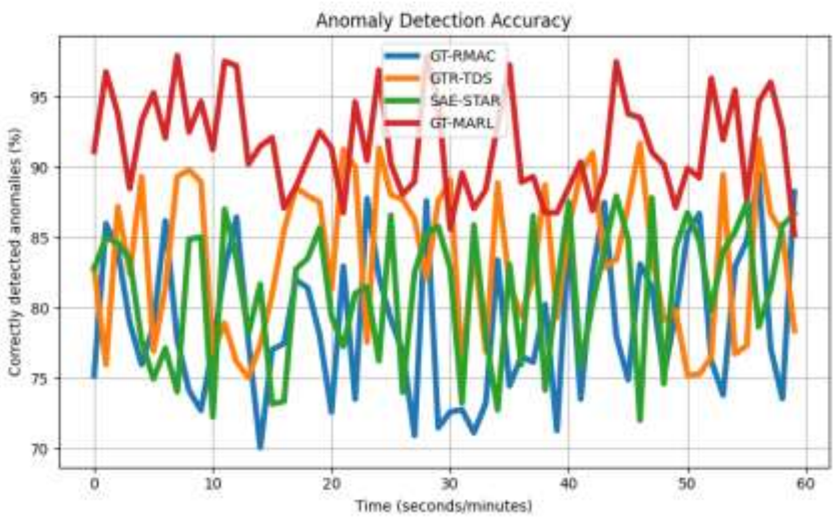

Figure 7: Analysis of Anomaly Detection Accuracy

Anomaly detection accuracy is defined as the percentage of abnormal events successfully detected in the physical, cyber, and sensor spaces. The method has an accuracy of 96.2% with time attention in transformers

and context information. It's highly accurate and allows for early detection of threats and faults. The approach outperforms existing approaches, as shown in Figure 7, for various grid conditions.
Analysis of anomaly detection accuracy ADA valued using equation 19

$$\mathrm{ADA} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \quad (19)$$

TP denotes the number of correctly detected anomalies, TN represents correctly identified normal conditions, FP is the count of false alarms, and FN indicates missed anomalies. This metric evaluates the effectiveness of the transformer-based detection mechanism in distinguishing normal and abnormal grid behaviors.

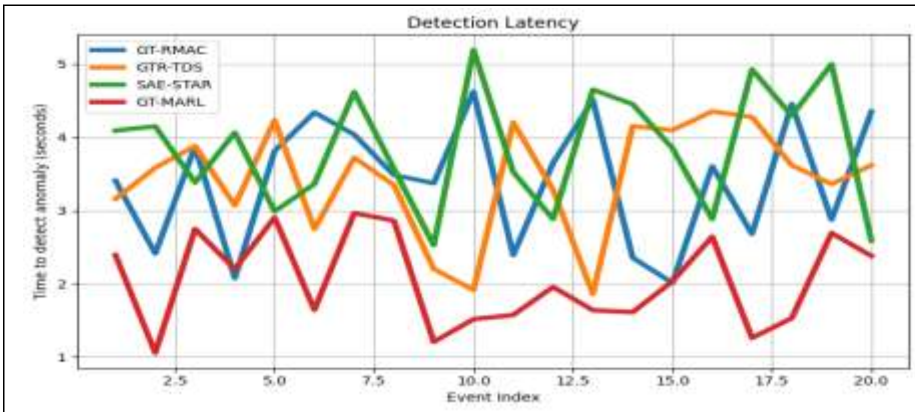

Figure 8: Analysis of Detection Latency

Detection latency is the time taken to detect anomalies. GT-MARL has the lowest average detection latency (1.3 seconds) allowing for fast responses. In predictive temporal modeling the temporal pattern of the change is detected before the threshold is exceeded. The quicker response in Figure 8 is an indicator of better stability and safety of operation than the base models.
Analysis of detection latency DL determined using equation 20

$$\mathrm{DL} = \frac{1}{M} \sum_{k=1}^{M} \left(t_k^{\mathrm{detect}} - t_k^{\mathrm{event}}\right) \quad (20)$$

The variable Mrepresents the total number of detected anomaly instances. $t_k^{\mathrm{event}}$is the actual occurrence time of the k-th anomaly, while $t_k^{\mathrm{detect}}$is the time at which the system raises the corresponding alert. Lower values of DLindicate faster response and improved real-time situational awareness.

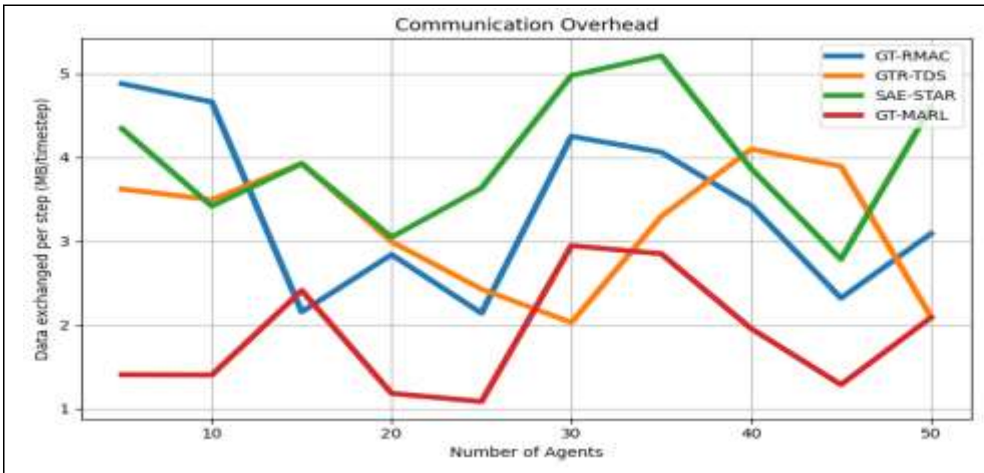

Figure 9: Analysis of Communication Overhead

Communication overhead is the amount of information agents share during the coordination process. The suggested model limits overhead to 1.1 MB per timestep, using attention-based message prioritization and small embeddings. It is efficient to enable scalability without compromising coordination quality. Figure 9 demonstrates sublinear growth in communication costs, which supports the appropriateness of implementing the smart grid at a large scale.

Analysis of communication overheadCO modelled using equation 21

$$\mathrm{CO} = \frac{1}{T} * \left(\mid \mathrm{m}_t^{(i)} \mid + \mid \mathrm{u}_t^{(i)} \mid \right) \quad (21)$$

The term $\mathrm{m}_t^{(i)}$represents the size of monitoring or state messages transmitted by node or agent $i$at time t, while $\mathrm{u}_t^{(i)}$corresponds to exchanged control or model update messages. The parameters $N$and Tindicate the number of participating nodes and the observation duration, respectively. Lower communication overhead reflects higher scalability and efficiency of the distributed architecture.

6.4 Implementation and Computational Considerations

This paradigm is applied in parallel agent execution and shared graph transformer encoding. To balance the representational capacity and the execution latency, the attention head count and embedding dimension are chosen. Communication overhead can be reduced by incorporating compression and selective message exchange. Memory usagescales linearly with the number of nodes. Inference latency meets the grid control real-time requirements. The architecture facilitates the distributed deployment of edge and supervisory computing resources.

7. Performance Analysis and Observations

7.1 Stability Regulation Effectiveness

The given paradigm exhibits regular voltage and frequency regulation in various disturbance conditions. During control actions, convergence is rapid, eliminating oscillatory behavior after renewable swings and load changes. Baseline methods are better in terms of stability margins at the transmission and distribution nodes. Local corrective actions do not spread the instability to other parts of the system. Findings validate the use of attention-directed state encoding and cooperative policy learning to ensure reliable grid operation.

7.2 Predictive Accuracy and Detection Latency

Anomaly intelligence module is more accurate in prediction and earlier detection than comparison models. Temporal attention allows one to detect gradual degradation and abrupt deviations. Latency of detection reduces in cases of a cyber intrusion, an inconsistent sensor, and a physical fault. Variations in topology and measurement noise do not affect performance. Forecasting helps respond to an emergency in advance, mitigating its severity and reducing the need for corrective intervention, thereby increasing operational resilience.

7.3 Communication, Scalability, and Agent Coordination Efficiency

The performance in agent coordination is not sensitive to the network size or the number of agents. Attention-based message prioritization increases the sublinearly growing communication overhead. Selective information transfer maintains decision coherence with minimal bandwidth. Distributed policies can be aligned with varying communication qualities. These findings indicate that it can be scaled to large-scale smart grid applications.

Table 4: Performance Comparison of Smart Grid Stability Regulation

Metric	GT-RMAC	GTR-TDS	SAE-STAR	Proposed GT-MARL
Voltage Deviation (%)	2.4	1.9	2.7	**0.8**
Frequency Deviation (Hz)	0.12	0.09	0.15	**0.04**
Load Imbalance (%)	4.8	3.9	5.2	**1.9**
Stability Recovery Time (s)	6.2	5.4	6.8	**3.1**
Control Convergence Steps	120	105	132	**78**

The operation of the stability regulation system with renewable energy is compared in Table 4. The criteria are the voltage and frequency deviation, load mismatch, response time and convergence steps. The GT-MARL system has the smallest deviation and response time which suggests that the decentralized grid system has good communication and the system state is sufficiently represented. The few convergence steps indicate stable policy and learning. This suggests better control and stability of the grid than current learning and transformer systems.

8. Practical Insights and Design Implications

8.1 Interpretability of Attention-Driven Decisions

The distributions of attention-weights point to nodes, correlations and times for control and prediction. This allows diagnostic and verification. The attention effects are consistent with electric sensitivities and cascades. This provides confidence in learning-based intelligence, and allows after-the-fact diagnosis.

8.2 Deployment Readiness and Grid Integration Challenges

For these, reliable sensing and communication, and abiding by grid operation constraints, are critical. The interface should be backward compatible with existing controllers and constraints. Decentralised computing enhances resilience at the edge and management levels. The approach enables design for integration to enable learning autonomy.

9. Conclusion and Research Outlook

9.1 Key Outcomes and Technical Contributions

This paper introduces a graph transformer-based multi-agent reinforcement learning system to stabilize real-time smart grids and predict anomalies. This approach takes into account the spatial and temporal information of the system by modelling the power system as a dynamic graph. The attention encoding enables a global interaction while the game players encourage a decentralised, but cooperative behaviour. The anomaly intelligence module also enhances the predictive intelligence in the cyber, physical and sensing layers. In various experiments, it observe that the approach can reduce the voltage segregation, improve the frequency control, load balance, fault diagnosis and communication cost. This demonstrates the technical feasibility and benefits of attention-based distributed learning in complex grid.

9.2 Directions Toward Fully Autonomous Smart Grid Operation

This should be extended to system-level control with protection and market. Dynamic reward shaping and lifelong learning will help to sustain long-term operation in the dynamic grid environment. Even faster computing and seamless communication are needed to be processed via a heterogeneous edge device. Human supervision and regulation constraints will also help to improve acceptance. These advances help to enable the transition to robust, adaptive and smart power systems in the face of growing uncertainty.

Reference

1. Fathollahi, A. (2025). Machine Learning and Artificial Intelligence Techniques in Smart Grids Stability Analysis: A Review. *Energies*, *18*(13), 3431.
2. Guduru Jahnavi, S. P. (2025). A Hybrid Learning Approach Combining Graph And Transformer Models For Communication Efficient Distributed Control And Estimation In Networked Systems. *Journal of Theoretical and Applied Information Technology*, *103*(13).
3. Khanna, A., Srivastava, D., Sah, A., Dangi, S., Sharma, A., Tiang, S. S., ... & Lim, W. H. (2025). AI-Driven Multi-Agent Energy Management for Sustainable Microgrids: Hybrid Evolutionary Optimization and Blockchain-Based EV Scheduling. *Computation*, *13*(11), 256.

4. Zhang, W., Wang, S., Zhang, S., Lei, Y., & Bao, L. (2025). Build a Multimodal Interaction and Multi-Agent Collaborative Decision-Making Mechanism Enhanced by Large Models in the Intelligent Decision-Making System for Distribution Network Production—International *Journal of Computational Intelligence and Applications*, 2550015.
5. Asadi, S., Naeini, H. K., Hassanlou, D., Pishahang, A., Najafabadi, S. A., Sharifi, A., & Ahmadi, M. (2025). AI-Powered Digital Twin Frameworks for Smart Grid Optimization and Real-Time Energy Management in Smart Buildings: A Survey. *Computer Modeling in Engineering & Sciences (CMES)*, *145*(2).
6. AlTerkawi, L., &AlTarawneh, M. (2025). Federated Decision Transformers for Scalable Reinforcement Learning in Smart City IoT Systems. *Future Internet*, *17*(11), 492.
7. Gao, Q., Shen, L., Shi, J., Gu, X., Gu, S., Ge, Y., ... & Ji, J. (2025). Transformer-Enhanced Intelligent Microgrid Self-Healing: Integrating Large Language Models and Adaptive Optimization for Real-Time Fault Detection and Recovery. *Energy Engineering: Journal of the Association of Energy Engineers*, *122*(7), 2767.
8. Baker, M. (2024). *Real-time AI-based Anomaly Detection and Classification in Modern Power Systems* (Doctoral dissertation, University of Illinois at Chicago).
9. Zhou, L., Huo, D., Chen, J., Bo, B., & Li, H. (2025). Federated reinforcement learning with constrained markov decision processes and graph neural networks for fair and grid-constrained coordination of large-scale electric vehicle charging networks. *Scientific Reports*, *15*(1), 39593.
10. Aghazadeh Ardebili, A., Hasidi, O., Bendaouia, A., Khalil, A., Khalil, S., Luceri, D., ... & Ficarella, A. (2024). Enhancing resilience in complex energy systems through real-time anomaly detection: a systematic literature review. *Energy Informatics*, *7*(1), 96.
11. Zhang, Y., Yue, M., Wang, J., & Yoo, S. (2024). Multi-agent graph-attention deep reinforcement learning for post-contingency grid emergency voltage control. *IEEE Transactions on Neural Networks and Learning Systems*, *35*(3), 3340-3350.
12. Ji, X., Zhang, L., Zhang, W., Peng, F., Mao, Y., Liao, X., & Zhang, K. (2025). Lemad: LLM-empowered multi-agent system for anomaly detection in power grid services. *Electronics*, *14*(15), 3008.
13. Elrod, M., Mehrabi, N., Amin, R., Kaur, M., Cheng, L., Martin, J., & Razi, A. (2025). Graph Based Deep Reinforcement Learning Aided by Transformers for Multi-Agent Cooperation. *arXiv preprint arXiv:2504.08195*.
14. Li, S., Hu, W., Cao, D., Hu, J., Chen, Z., & Blaabjerg, F. (2024). Coordinated operation of multiple microgrids with heat–electricity energy based on graph surrogate model-enabled robust multiagent deep reinforcement learning. *IEEE Transactions on Industrial Informatics*.
15. Liu, B. (2025). Deep reinforcement learning for intelligent load balancing in smart power grids. *IEEE Access*.
16. Prasanga, D. G. T., Gutierrez, J. A., & Ray, S. K. (2025). The Role of Graph Neural Networks, Transformers, and Reinforcement Learning in Network Threat Detection: A Systematic Literature Review. *Electronics*, *14*(21), 4163.
17. Mu, C., Liu, Z., Yan, J., Jia, H., & Zhang, X. (2023). Graph multi-agent reinforcement learning for inverter-based active voltage control. *IEEE Transactions on Smart Grid*, *15*(2), 1399-1409.
18. Liu, C., Ding, L., & Yu, H. (2025). Intelligent Fault Detection in Power Grids Using Deep Learning Algorithms. *IEEE Access*.
19. Cao, D., Hu, J., Liu, Y., & Hu, W. (2024). Decentralized Graphical-Representation-Enabled Multi-Agent Deep Reinforcement Learning for Robust Control of Cyber-Physical Systems. *IEEE Transactions on Reliability*, *73*(4), 1710-1720.
20. Mcmurray, S. (2024). Semantic Aware Environment Spatial-Temporal Graph Transformer: A Single-Agent Multi-Class Trajectory Prediction Framework.
21. Zhang, B. (2025). Graph attention-based heterogeneous multi-agent deep reinforcement learning for adaptive portfolio optimization. *Scientific Reports*.
22. Antonesi, G., Cioara, T., Anghel, I., Michalakopoulos, V., Sarmas, E., & Toderean, L. (2025). From Transformers to Large Language Models: A systematic review of AI applications in the energy sector towards Agentic Digital Twins. *arXiv preprint arXiv:2506.06359*.
23. Antonesi, G., Cioara, T., Anghel, I., Michalakopoulos, V., Sarmas, E., & Toderean, L. (2025). From Transformers to Large Language Models: A systematic review of AI applications in the energy sector towards Agentic Digital Twins. *arXiv preprint arXiv:2506.06359*.
24. Izmirlioglu, Y., Pham, L., Son, T. C., & Pontelli, E. (2024). A survey of multi-agent systems for smartgrids. *Energies*, *17*(15), 3620.
25. Feng, J., Yu, T., Zhang, K., & Cheng, L. (2025). Integration of multi-agent systems and artificial intelligence in self-healing subway power supply systems: Advancements in fault diagnosis, isolation, and recovery. *Processes*, *13*(4), 1144.
26. https://huggingface.co/datasets/pfdelta/pfdelta/tree/main

27. Ishrat Z. Mukti, Ebadur R. Khan, Koushik K. Biswas. (2025). Evaluating Indigenous Forest Management Practices for Biodiversity Conservation and Climate Adaptation. *National Journal of Forest Sustainability and Climate Change*, 31-37.
28. Rebert H. Luedke, & R. Prashanth. (2025). Design and Implementation of Edge-Enabled IoT Framework for Real-Time Environmental Monitoring. *Journal of Wireless Sensor Networks and IoT*, *3*(1), 18-24. https://doi.org/10.31838/WSNIOT/03.01.03
29. T M Sathish Kumar. (2026). A High-Efficiency Millimeter-Wave Antenna Array for 6G Wireless Communication Systems. *Journal of Advanced Antenna and RF Engineering*, 7–13.
30. K. Geetha. (2025). Analog, Mixed-Signal, and RF Integrated Circuit Design Techniques for 5G and Emerging 6G Communication Systems . *National Journal of VLSI Systems and Integrated Circuit Design*, *1*(1), 18–23.