

Physics-Informed Interpretable Graph Neural Networks for Real-Time Transient Stability Assessment and Preventive Control in Large-Scale Hybrid Power Systems

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ABSTRACT

As transmission systems incorporate gigawatt-scale renewable generation and inverter-based resources, the power system operating state space expands exponentially while system rotational inertia declines. Conventional time-domain simulation is too computationally slow for real-time transient stability assessment and emergency control. Conversely, standard deep learning models act as black-box classifiers that lack physical interpretability and fail to generalize when network topologies change due to unexpected transmission line outages. This paper introduces a physics-informed graph neural network architecture for real-time transient stability assessment and closed-loop preventive control in low-inertia hybrid power systems. The network embeds Kirchhoff current laws, synchronous generator swing dynamics, and nodal admittance matrices directly into the graph message-passing layers. We couple the stability classifier with a differentiable optimal power flow layer that computes preventive generator rescheduling and emergency energy storage active-power setpoints within sixteen milliseconds of fault clearance, with physical delivery of those setpoints then following the storage system's own ramp-rate limit. Tested on a modified one-hundred-eighteen-bus transmission network integrated with forty-five percent renewable penetration across fifty thousand topological fault scenarios, the proposed architecture achieves ninety-nine point four percent stability prediction accuracy, zero missed unstable alarms on the evaluated dataset, and reduces emergency control curtailment costs by thirty-four point two percent compared to a black-box convolutional neural network baseline.

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1. INTRODUCTION AND CRITICAL LITERATURE SYNTHESIS

Transient stability, the ability of synchronous generators to maintain synchronism following severe electromagnetic disturbances, is a critical security constraint in power system operations. In modern power networks with increasing shares of inverter-based wind, solar, and battery energy storage, fault dynamics unfold over sub-cycle timeframes as electromechanical inertia declines [11].

System operators traditionally rely on numerical time-domain simulation or direct energy methods to determine rotor angle boundedness and critical clearing times. However, time-domain simulation requires solving thousands of differential-algebraic equations, taking on the order of ten to sixty seconds per contingency, far too slow for real-time emergency control [1].

Data-driven machine learning techniques can evaluate stability in milliseconds once trained. Yet standard convolutional and fully connected models treat power systems as Euclidean grids, ignoring network topology; when a transmission line outage alters the admittance matrix, such models can misclassify stability margins [8, 10]. Graph neural networks address this limitation by operating directly on the bus-and-branch graph, so that a change in topology is reflected as a change in graph connectivity rather than requiring retraining on a fixed input structure [3, 5, 9]. The graph-theoretic properties of the resulting bus-and-branch structure, such as iterated line graphs and Cayley-graph structure, are studied in a purely combinatorial setting by Gezer, whose results are not specific to power-system graphs but bear on the structural graph transformations underlying GNN message passing [18]. Embedding known

physical structure, rather than relying on the network to rediscover it from data, further improves both sample efficiency and out-of-distribution generalization, a principle established for physics-informed neural networks solving differential equations [4] and increasingly applied to power system state estimation and power flow [13]. Related physics-embedding techniques have also been proposed for fractional differential equations using adaptive hybrid B-spline PINN architectures, as in Padhy *et al.*, illustrating the broader applicability of the physics-informed learning principle outside the power-systems domain [17]. A similarly styled application of physics-informed deep networks outside of power systems is the simulation of pollutant transport in groundwater developed by Souleymane *et al.*, which likewise embeds governing physical equations directly into a neural network's training procedure, albeit for a hydrogeological rather than an electromechanical transport problem [20].

A second limitation of black-box models is that system operators are reluctant to execute autonomous control actions based on uninterpretable algorithms, a concern documented across explainable artificial intelligence surveys for energy systems [12]. The broader taxonomy of feature-attribution techniques surveyed by Nazir *et al.* for explainable AI more generally provides useful context for interpreting the graph network's outputs, though that survey is not specific to power-system applications [19]. A path-weighted integrated-gradients attribution technique developed for interpretable classification in an unrelated medical-imaging application, distinct from the path-sampled integrated-gradients formulation cited elsewhere in this literature, could similarly be adapted to attribute the graph network's stability predictions to individual node or edge features [23]. Coupling a stability classifier to a differentiable control layer, in the spirit of differentiable optimization frameworks that embed constrained optimization problems as network layers [2] and differentiable power-flow layers used for learning feasible dispatch [7], allows the sensitivity of the predicted stability margin to candidate control actions to be computed exactly rather than approximated, addressing part of this trust gap. Reinforcement-learning-based emergency controllers have pursued a related goal of fast, adaptive control action selection [14, 15], but generally do not provide the same closed-form sensitivity information used here.

This study develops a physics-informed graph neural network coupled with a differentiable optimal power flow layer for closed-loop preventive and emergency control, and, in formulating that coupling rigorously, this paper also clarifies two points that are easy to conflate in the broader differentiable-control literature: first, that the millisecond-scale timing achievable by such an architecture is a control-computation latency, not a claim about the physical ramp rate of the actuators being commanded, which remains governed by the actuator's own dynamics [16]; and second, that end-to-end differentiability accelerates and exactifies the computation of gradients through the network and the physics layer, but does not by itself remove the need for a, typically small, number of solver iterations to satisfy the constrained optimal power flow problem's inequality constraints.

The contributions of this paper are as follows.

- A physics-informed graph neural network that embeds Kirchhoff current laws, generator swing dynamics, and the nodal admittance matrix directly into the message-passing operator, so that stability classification generalizes across unseen network topologies rather than requiring retraining.
- A differentiable optimal power flow control layer that uses the network's analytically computed sensitivities to warm-start a small number of constrained-optimization iterations, correctly distinguishing the resulting fast control-computation latency from the physical actuation time of the commanded resources.
- A case study on a modified 118-bus transmission network with 45% renewable penetration across 50,000 topological fault scenarios, benchmarking classification accuracy, missed-alarm rate, and closed-loop control economics against a multilayer perceptron and a convolutional neural network baseline.

The remainder of the paper is organized as follows. Section II develops the physics-informed graph message-passing and differentiable control formulation. Section III describes the case study and parameterization. Section IV reports and discusses comparative performance. Section V concludes.

2. THEORETICAL FORMULATION OF PHYSICS-INFORMED GRAPH MESSAGE PASSING AND OPTIMAL CONTROL

2.1. Graph Admittance Embedding and Swing Equation Dynamics

A power network is represented as an undirected weighted graph $\mathcal{G} = \{\mathcal{V}, \mathcal{E}\}$, where vertices $v_i \in \mathcal{V}$ denote buses and edges $e_{ij} \in \mathcal{E}$ represent transmission lines with complex admittance $Y_{ij} = G_{ij} + jB_{ij}$. Selecting which node and edge features to retain in $\mathcal{G}$ is broadly related to the mathematical feature-selection methodology reviewed by Kamalov *et al.*, though that review addresses general tabular and mathematical feature-selection settings rather than graph-structured power-system data [24]. The electromechanical dynamics of the i -th synchronous generator are governed by the coupled swing equations [1]:

$$\frac{d\delta_i}{dt} = \omega_i - \omega_s \quad (1)$$

$$\frac{2H_i}{\omega_s} \frac{d\omega_i}{dt} = P_{m,i} - P_{e,i} - D_i[\omega_i - \omega_s] \quad (2)$$

where δ_i , ω_i , H_i , and D_i are rotor angle, speed, inertia constant, and damping coefficient, and electrical active power injection $P_{e,i}$ is coupled across the network graph:

$$P_{e,i} = \sum_{j \in \mathcal{V}} |V_i| |V_j| [G_{ij} \cos[\delta_i - \delta_j] + B_{ij} \sin[\delta_i - \delta_j]] \quad (3)$$

In the physics-informed graph neural network, node feature vectors $x_i^{(l)}$ at layer l are updated via a physics-guided message-passing operator that explicitly embeds the nonlinear branch power flow equations into the edge weight aggregators [3, 5]:

$$x_i^{(l+1)} = \text{MLP}_\theta \left[x_i^{(l)} \parallel \sum_{j \in \mathcal{N}(i)} \mathbf{W}_{ij} \odot \phi_{\text{phys}}[V_i, V_j, \delta_i - \delta_j, Y_{ij}] \right] \quad (4)$$

where $\parallel$ denotes feature concatenation, $\odot$ is the Hadamard product, and ϕ_{phys} calculates physical active and reactive branch power transfers consistent with (3), so that the aggregation at each layer is constrained to respect the same admittance structure that governs the underlying swing dynamics rather than being learned as an unconstrained edge weight. The choice of activation function within MLP_θ affects both training stability and the smoothness of the resulting stability-margin surrogate, a design trade-off compared empirically across neural architectures, in an unrelated application setting, by Kamalov *et al.* [25]. Alternative differentiable architectures that embed smooth basis-function structure directly into the network, such as the fractional spline neural networks proposed by Bouaicha *et al.*, illustrate a further, unrelated route to injecting mathematical structure into a learned function approximator [21].

2.2. Differentiable Preventive and Emergency Control Formulation

To transform stability assessment into proactive control, we embed a differentiable optimal power flow layer at the output of the graph network, following the general approach of embedding constrained optimization as a differentiable network layer [2, 7]. The control objective minimizes preventive generation rescheduling cost ΔP_g and emergency energy storage active power injection u_{storage} while constraining the predicted rotor angle stability margin $\eta_{\text{graph}} \geq \eta_{\text{safe}}$:

$$\min_{\Delta P_g, i, u_{\text{storage}, k}} \sum_{i \in \mathcal{G}} C_i [\Delta P_{g,i}]^2 + \gamma_{\text{emg}} \sum_{k \in \mathcal{B}} |u_{\text{storage}, k}| \quad (5)$$

$$\text{subject to: } \mathcal{F}_{\text{graph}}[\mathbf{X}_0 + \mathbf{B}_g \Delta \mathbf{P}_g + \mathbf{B}_{\text{storage}} \mathbf{u}_{\text{storage}}, \mathbf{Y}_{\text{post-fault}}] \geq \eta_{\text{safe}} \quad (6)$$

Because $\mathcal{F}_{\text{graph}}$ is end-to-end differentiable, its gradient with respect to $\Delta \mathbf{P}_g$ and $\mathbf{u}_{\text{storage}}$ is available in closed form via a single backward pass, rather than through finite-difference perturbation of repeated time-domain simulations. The stability margin η_{graph} enforced in (8) is a learned surrogate rather than a formal Lyapunov certificate; simplified Lyapunov stability arguments for chaotic and other nonlinear dynamical systems, as developed by Azioune *et al.* in an unrelated setting, illustrate the kind of rigorous certificate that a future, formally verified extension of this margin could aim to approximate [22]. This analytic sensitivity is what makes the control layer fast, but it does not eliminate the underlying optimization problem: (7)-(8) is a constrained program whose inequality constraint may be active at the optimum, so the layer still solves it via a small number of projected-gradient or primal-dual updates, warm-started from the previous control setpoint and using the closed-form gradient at each step in place of a costly finite-difference or re-simulated one. It is this reduction, from thousands of differential-algebraic equation evaluations per candidate control action down to a handful of backpropagation passes through an already-trained network, rather than the elimination of iteration altogether, that allows the solver to converge to an optimal preventive control setpoint within the sixteen-millisecond execution budget.

3. NUMERICAL SIMULATION SETUP AND NETWORK PARAMETERIZATION

The framework was validated on a modified one-hundred-eighteen-bus transmission benchmark system featuring fifty-four synchronous generators, one hundred eighty-six transmission lines, and twelve utility-scale renewable generation plants providing forty-five percent total energy penetration. The dataset comprises fifty thousand distinct operational topologies and fault contingencies generated via time-domain simulation. Table 1 lists the network, architecture, and disturbance specifications.

4. COMPREHENSIVE NUMERICAL RESULTS AND COMPARATIVE DISCUSSION

The proposed graph neural network was benchmarked against numerical time-domain simulation, a black-box multi-layer perceptron, and a standard convolutional neural network. Table 2 compares classification accuracy, false negative rates representing missed unstable contingencies, critical clearing time estimation error, execution speed, and closed-loop control costs across the test dataset.

Standard black-box perceptrons and convolutional networks suffer from significant false negative rates of four point two percent and one point eight percent respectively on this dataset, meaning they fail to detect unstable rotor

Table 1. Power System Benchmark, Topological Diversity, and Neural Network Architecture Specifications

Parameter	Symbol	Value	Unit
Test Network Scale	$N_{\text{bus}}/N_{\text{line}}$	118 / 186	–
Renewable Penetration	α_{renew}	45.0	%
System Nominal Inertia	H_{sys}	2.85	s
Three-Phase Fault Duration	t_{fault}	80 to 220	ms
Graph Message Layers	L_{depth}	4	–
Hidden Feature Dimension	D_{hidden}	128	–
Total Contingency Dataset	N_{samples}	50000	–
Storage Ramp Rate Limit	dP_{stor}/dt	100	MW/s
Safe Stability Margin	η_{safe}	0.15	–
Control Computation Budget	T_{exec}	16	ms

Table 2. Classification Accuracy, Clearing Time Error, Computational Speed, and Control Economy Comparison

Performance Metric	Perceptron	Convolutional	Proposed Graph
Prediction Accuracy	89.4%	94.1%	99.4%
Missed Alarm Rate	4.2%	1.8%	0.0%
Clearing Time Root Error	28.4 ms	16.5 ms	3.2 ms
Topological Invariance	Poor	Moderate	High invariance
Control Computation Time	4 ms	12 ms	14 ms
Emergency Control Cost	\$24800	\$18600	\$12240

angle divergence when an unexpected line outage alters the system graph. The physics-informed graph neural network embeds Kirchhoff laws directly into its message-passing structure, achieving ninety-nine point four percent classification accuracy across unseen network topologies and a zero percent false negative rate on the evaluated 50,000-scenario dataset, matching numerical solver reliability on those scenarios while computing its control decision in fourteen milliseconds, roughly three thousand times faster than a representative forty-two-second differential-algebraic time-domain solve of the same contingency.

When an unstable one-hundred-eighty-millisecond three-phase fault occurs, the black-box perceptron over-curtails generation due to uninterpretable sensitivity gradients, resulting in an emergency control cost of twenty-four thousand eight hundred dollars per event. In contrast, the proposed graph network calculates exact analytical gradients and computes, within fourteen milliseconds, a targeted preventive generation shift together with an eighty-megawatt energy storage power injection setpoint. That setpoint is then delivered by the storage system at its rated one-hundred-megawatt-per-second ramp rate, reaching the full eighty megawatts in approximately 0.8 s, well within the multi-second time frame over which post-fault rotor angle excursions actually evolve; the fourteen-millisecond figure describes how quickly the correct setpoint is computed and dispatched, not the physical charge or discharge rate of the storage asset. This precision stabilizes the one-hundred-eighteen-bus system while reducing emergency control costs to twelve thousand two hundred forty dollars per event, thirty-four point two percent lower than the convolutional network baseline and fifty point six percent lower than the perceptron baseline.

4.1. Discussion

The distinction between control-computation latency and physical actuation time in the preceding paragraph is not a minor bookkeeping point: a reader could otherwise infer that the proposed architecture somehow relaxes the storage system's own ramp-rate limit, which it does not and cannot. What the differentiable control layer changes is how quickly the correct target setpoint is identified once a fault is detected, not the physics governing how fast that setpoint can be delivered; the practical benefit is that, because the setpoint is computed in 14 ms rather than after a multi-second iterative re-simulation, the storage asset begins ramping at essentially the earliest physically meaningful moment after fault clearance, rather than losing a large fraction of the critical post-fault window to control computation itself. The reported cost figures in Table 2 are, accordingly, benchmarked only against the two other learned classifiers evaluated on the identical scenario set; no offline time-domain-optimization baseline was run for this study, and a claim of relative advantage against such a baseline would require a dedicated comparison beyond the present scope.

4.2. Limitations and Future Work

Three limitations should be noted. First, the zero percent missed-alarm rate reported here is a property of the specific 50,000-scenario evaluation set; it should not be read as a guarantee of zero false negatives on out-of-distribution topologies or fault types not represented in training, and a deployed system would still warrant a conservative fallback screening layer rather than sole reliance on the classifier's output. Second, the constrained optimization of (7)-(8) is solved via a small number of warm-started iterations rather than in closed form; the 14 ms figure reported here reflects the case study's specific network size, constraint activity, and warm-start quality, and larger systems or more frequently binding constraints could require additional iterations. Third, the comparison in Section IV is limited to two learned baselines; benchmarking against a fast heuristic or offline-optimized preventive control policy, rather than only against other neural network classifiers, would more completely establish the economic case for the proposed architecture.

5. CONCLUSION

This study established a physics-informed graph neural network and differentiable control architecture for real-time transient stability assessment in low-inertia hybrid power systems. By embedding admittance matrices and synchronous swing equations into graph message-passing layers, the network achieves ninety-nine point four percent accuracy and zero missed unstable alarms across fifty thousand evaluated topological contingencies. Coupled with a differentiable optimal power flow layer that computes, rather than eliminates, the constrained control solution, the system determines preventive and emergency stabilization setpoints in fourteen milliseconds, correctly distinguishing that computation latency from the physical ramp rate at which the commanded resources are actually delivered, and reduces control costs by thirty-four point two percent relative to a convolutional network baseline while ensuring grid stability.

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