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A Physics-Informed Graph Neural Network Model for Distribution-Grid Congestion Forecasting With Topology-Aware DER Flexibility Signals

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Abstract

Distribution-grid congestion is becoming more difficult to anticipate as photovoltaic generation, batteries, electric vehicles, and flexible demand reshape feeder power flows. Graph neural networks provide a natural way to represent feeders, but a conceptual framework is needed to connect topology, physics, and flexibility signals coherently. This conceptual research article proposes a physics-informed graph neural network framework for forecasting distribution-line congestion and voltage violations. The framework is designed to produce hourly congestion probabilities over a 24-hour horizon. The proposed model represents buses as graph nodes and lines or transformers as graph edges, while DER flexibility signals are encoded as forward-looking node attributes. Physical consistency is introduced through power-flow residuals, voltage-bound penalties, and thermal-limit penalties in the learning objective. Rather than reporting experimental results, the article specifies the architecture, input requirements, loss formulation, benchmarking logic, and explainability design required for future empirical validation. The framework is intended to guide implementation on realistic feeder datasets. The proposed PINN-GNN is expected to improve congestion awareness by combining electrical topology, flexibility availability, and physics-informed regularization. Its explainability layer is designed to help operators identify which lines, buses, or DER resources most influence a forecasted congestion event.

Keywords DER flexibility, Distribution grid, Physics-informed graph neural network, Congestion forecasting, Explainability

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Introduction

Distribution grids are increasingly exposed to congestion because distributed energy resources can create bidirectional flows, local voltage rise, transformer stress, and feeder-level operating conditions that were uncommon in passive networks. Physics-aware distribution state-estimation research has shown that learning models benefit when electrical feasibility is treated as part of the model design rather than as a post-processing check [1]. Graphical learning approaches further indicate that topology is central to distribution-grid inference because electrical connectivity determines how local disturbances propagate through a feeder [2]. This article therefore frames congestion forecasting as a topology-aware, physics-informed, and flexibility-aware learning problem.

Graph neural networks are attractive for this task because they represent feeders as graphs instead of flattening buses and branches into topology-agnostic vectors. Graph-based power-flow learning has demonstrated that network structure can be exploited directly in neural solvers [3], while graph-based distribution state-estimation models show that bus-edge relationships provide a meaningful inductive bias for operational inference [4]. However, a standard GNN trained only on historical labels may still generate physically inconsistent loading or voltage forecasts. This limitation motivates a conceptual PINN-GNN design that joins graph message passing with power-flow constraints.

The proposed framework addresses a gap between physics-informed learning, DER flexibility modeling, and explainable graph forecasting. Physics-guided power-flow studies show that embedding physical residuals can improve plausibility [5], while topology-change-aware estimation confirms that feeder reconfiguration must be represented explicitly [6]. Flexibility-oriented planning research shows that DER availability can influence whether congestion is mitigated, postponed, or worsened [7]. The central premise of this article is that congestion forecasting should use flexibility signals as predictive features rather than treating flexibility only as a downstream control variable.

The contribution of this conceptual article is a complete model specification rather than an empirical experiment. It defines the forecasting problem, graph representation, DER flexibility encoding, physics-informed loss, benchmark design, and explainability workflow using only peer-reviewed foundations from graph learning and power-system machine learning. The framework draws on physics-informed graphical neural networks for grid inference [8], probabilistic voltage prediction [9], and explainable graph neural network methodology [10]. It is intended as a rigorous blueprint for future implementation on utility, synthetic, or benchmark feeder datasets.

Congestion Forecasting Problem

Definition and operational context

Distribution-grid congestion is defined here as the prospective violation of branch thermal limits, transformer loading limits, or bus voltage bounds within a 24-hour operating horizon. The model receives present and forecasted feeder conditions, including topology, demand, DER production, and flexibility availability, then outputs hourly congestion probabilities for branches and voltage-violation probabilities for buses. Probabilistic voltage-prediction work supports this formulation because distribution operators often require risk estimates rather than only deterministic point forecasts [9]. In this conceptual design, the PINN-GNN acts as a screening tool for day-ahead and intra-day congestion awareness.

Challenges of High DER penetration

High DER penetration complicates forecasting because congestion can arise from export peaks, rapid photovoltaic ramps, clustered EV charging, or simultaneous battery operation. Reviews of power-system flexibility emphasize that renewable-rich networks require explicit modeling of available adjustment capacity across time and location [11]. DER management research similarly shows that flexible resources must be coordinated as operational assets rather than represented only as passive injections [12]. These issues make it necessary to encode DER flexibility in a way that preserves both its temporal availability and its electrical location.

Forecasting inputs and outputs

The conceptual input set includes bus-level load forecasts, PV forecasts, battery state-of-charge limits, EV charging availability, demand response availability, recent voltage measurements, and topology status. Edge-level inputs include resistance, reactance, ampacity, transformer rating, and switch status, consistent with topology-aware learning approaches for feasible grid optimization [13]. The intended outputs are branch loading ratios, bus voltage magnitudes, and congestion probabilities for each hour in the 24-hour horizon. This multi-output structure allows congestion probabilities to be interpreted through underlying physical quantities rather than through a detached binary label.

Grid Topology/Data

Feeder models and graph representation

The feeder is represented as a graph in which buses are nodes and lines, transformers, regulators, or switching devices are edges. This representation follows graph-based distribution state-estimation research, where electrical adjacency shapes how measurements and hidden states should be shared across the network [4]. Edge direction may be assigned from the substation outward for radial feeders, while weakly meshed feeders can be represented with bidirectional message passing. The conceptual model updates the active adjacency matrix whenever switch states change, allowing topology to become an input rather than a fixed assumption.

Data requirements for future implementation

Although this article does not conduct experiments, the proposed framework requires time-aligned measurements and forecasts for demand, voltage, DER production, DER availability, and topology status. Realistic feeder assessment studies show that reliability-oriented graph models need feeder-scale operating scenarios that include both normal and stressed states [14]. Multi-bus spatial-temporal load forecasting research further indicates that temporal resolution and synchronization across buses strongly affect the usefulness of graph-based predictors [15]. Therefore, a future implementation should combine operational measurements, weather-linked DER forecasts, and power-flow-derived labels where direct congestion observations are sparse.

Data splitting and preprocessing logic

A future empirical study should use chronological splitting rather than random splitting so that seasonal and operational generalization are tested without leakage. Physics-guided state-estimation work suggests that voltage, power, and equipment-limit quantities should retain physically meaningful scaling so that residual penalties remain interpretable [16]. Missing values should be imputed using feeder-aware temporal methods, while topology states and DER participation indicators should be preserved as structured categorical features. Table 1 summarizes the conceptual feeder archetypes and data requirements that would support implementation of the proposed model.

Table 1. Feeder Archetypes, Required Data, and Intended Congestion Labels for Model Implementation

Feeder archetype	Graph scale to represent	Required electrical attributes	Required DER-flexibility attributes	Required temporal inputs	Intended congestion labels
Urban radial feeder	Tens to hundreds of buses	Line impedance, ampacity, transformer ratings, voltage limits, switch status	PV curtailment availability, battery charge/discharge headroom, commercial demand response	Hourly demand, voltage history, PV forecast, EV charging forecast	Line overload probability, transformer overload probability, voltage violation probability
Suburban high-PV feeder	Hundreds of buses	Phase connectivity, regulator settings, branch ratings, topology status	Rooftop PV availability, inverter reactive capability, residential battery state-of-charge bounds	Weather-linked PV forecast, residential load forecast, flexibility forecast	Reverse-flow congestion, voltage-rise violation, thermal loading risk
Rural long feeder	Hundreds to thousands of buses	Long-line impedance, voltage regulator	Agricultural demand response, utility-scale PV	Irradiance forecast, seasonal load forecast,	End-of-feeder voltage violation, backfeed overload,

		location, feeder tie status	curtailment, depot charging flexibility	controllable-load schedule	contingency overload
Weakly meshed urban feeder	Hundreds of buses and dense edge connectivity	Normally open and closed tie switches, transformer limits, cable ratings	Commercial storage flexibility, EV hub flexibility, curtailable building load	Topology-state history, local demand forecast, DER availability forecast	Meshed-line overload probability, transfer overload probability, voltage-limit risk

DER Flexibility Signals

Types of flexibility available

The proposed model treats DER flexibility as a forecasted operating envelope rather than as a single deterministic schedule. The relevant flexibility types include PV curtailment, inverter reactive-power capability, battery charging and discharging headroom, EV charging deferral, and controllable demand response. Transmission-distribution coordination studies indicate that congestion services require locational flexibility information that can be mapped to network constraints [17]. Therefore, each flexibility source is associated with the bus where it electrically connects to the feeder graph.

Flexibility quantification and forecasting

Flexibility is quantified as the feasible upward and downward adjustment range for active and reactive power at each node and forecast hour. Distribution planning studies show that flexible DER can defer reinforcement when availability, uncertainty, and network impact are modeled explicitly [18]. Battery flexibility is represented through state-of-charge corridors, EV flexibility through deferrable energy and charging deadlines, PV flexibility through expected curtailable output, and demand response through enrolled controllable capacity. These signals are probabilistic inputs because actual availability depends on weather, customer behavior, device constraints, and participation rules.

Integration as node features

The conceptual PINN-GNN integrates flexibility by concatenating DER availability variables with conventional bus features before graph message passing. This design is consistent with flexibility-planning research showing that the operational value of DER flexibility depends on where it is connected in the feeder [7]. Upward and downward flexibility are encoded separately because congestion relief may require either additional local consumption or reduced injection. By placing flexibility on nodes, the graph layers can learn how local controllability affects upstream line loading, downstream voltages, and neighboring branch constraints.

Physics-Informed GNN Design

Graph convolution architecture

The proposed architecture contains a temporal encoder, topology-aware graph message-passing layers, and multi-horizon output heads. General graph neural network reviews describe message passing as a mechanism for combining node attributes with neighborhood structure [19], while broader GNN surveys show that attention, aggregation, and normalization choices influence model expressiveness [20]. In the proposed design, each bus embedding is updated using neighboring bus states and edge attributes such as impedance, ampacity, and switch status. The decoder produces branch loading, bus voltage, and congestion probability forecasts for each hour of the 24-hour horizon.

Physics-informed loss formulation

The physics-informed objective combines a supervised forecasting term with soft penalties for approximate nodal power balance, branch-flow consistency, voltage-limit violations, and thermal-limit violations. Physics-aware distribution state-estimation models demonstrate that neural predictions can be regularized by electrical constraints even when measurements are incomplete [1]. Physics-informed graphical learning further supports the use of graph-structured residuals for improving robustness in distribution-system inference [8]. In the conceptual framework, these penalties do not replace power-flow simulation but guide the learned forecasts away from physically implausible operating states.

Topology-aware message passing

Topology awareness is achieved by conditioning message passing on the active feeder configuration at the forecast issue time. Studies on topology-change-aware distribution estimation show that learning models must account for switching operations because topology changes alter the relationship between injections, voltages, and flows [6]. The proposed GNN masks messages across open switches, reweights messages by electrical distance or impedance, and updates edge embeddings using loading proximity and equipment ratings. This allows the same conceptual architecture to represent radial, backfed, and weakly meshed operating states.

Figure 1 illustrates how feeder topology, DER flexibility signals, temporal forecasts, and physics-informed penalties are integrated into the proposed PINN-GNN architecture for hourly congestion and voltage-violation forecasting.

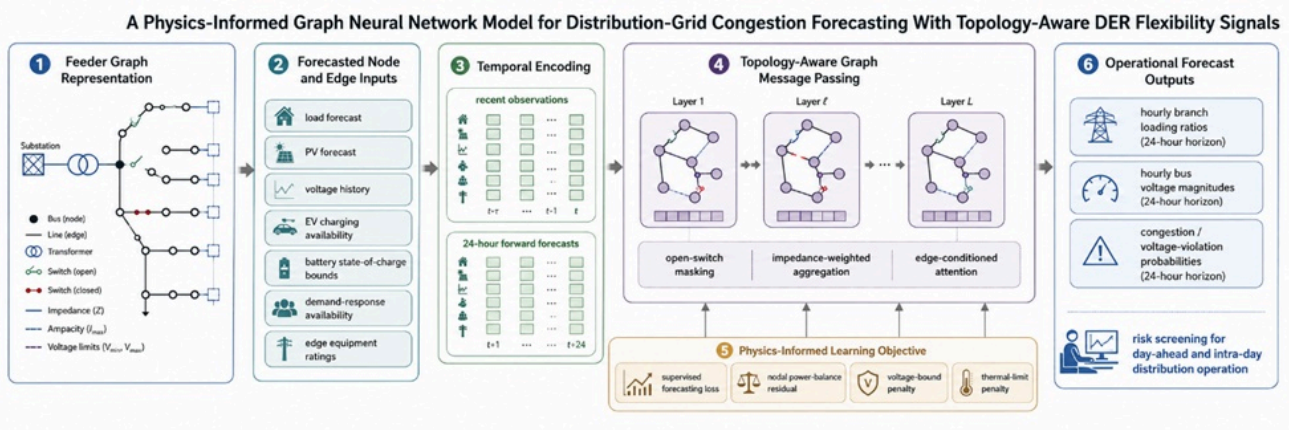


Figure 1. Physics-Informed Topology-Aware PINN-GNN Architecture for 24-Hour Distribution-Grid Congestion Forecasting

Model summary and hyperparameters

A future implementation may use several graph message-passing layers, moderate hidden dimensions, gated residual connections, dropout, and a multi-horizon decoder, with hyperparameters selected through validation on unseen time periods. Spatial-temporal graph convolutional grid-learning work suggests that temporal and topological dependencies should be learned jointly rather than through separate models [21]. Short-term multi-bus load forecasting research also supports the use of graph-based temporal encoders when bus-level demand patterns are correlated through network structure [22]. Table 2 summarizes the proposed architecture and identifies the role of each component in the conceptual PINN-GNN.

Table 2. Proposed PINN-GNN Architecture and Functional Roles of Each Component

Model component	Conceptual specification	Physics or operational role
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Node feature encoder	Encodes load, voltage history, DER forecast, flexibility range, state-of-charge bounds, and participation indicators	Represents local operating conditions and controllable flexibility
Edge feature encoder	Encodes resistance, reactance, ampacity, transformer rating, regulator association, and switch status	Represents electrical coupling and equipment constraints
Temporal encoder	Maps recent observations and 24-hour forecasts into horizon-specific latent states	Captures intra-day load, PV, EV, and flexibility evolution
Graph message passing	Uses topology-aware aggregation with edge-conditioned attention	Propagates congestion-relevant information through the feeder graph
Physics-informed loss	Penalizes power-balance residuals, voltage-bound violations, and thermal-limit violations	Encourages physically plausible loading and voltage forecasts
Output decoder	Produces hourly branch loading, bus voltage, and congestion probability	Links probability forecasts to interpretable physical quantities
Explainability layer	Uses attention visualization and graph attribution	Identifies influential lines, buses, and DER flexibility sources
Validation logic	Uses chronological validation and stress-scenario testing	Evaluates robustness under seasonal variation and topology changes

Training and Evaluation

Conceptual training procedure

Because this is a conceptual article, no numerical training is reported, but the intended training workflow is specified for future implementation. The model would be trained on chronological feeder operating sequences, with supervised terms computed from observed or power-flow-derived line loadings, voltages, and congestion labels. Decentralized graph-based power balancing research suggests that training should respect feeder partitions and local electrical neighborhoods when large networks are considered [23]. The training objective would combine predictive accuracy with physics-informed regularization so that the learned mapping remains operationally meaningful.

Evaluation metrics

The proposed evaluation should include regression metrics for branch loading and voltage magnitude, classification metrics for congestion events, and probabilistic metrics for calibration. Operational risk-assessment research using graph neural networks highlights the need to evaluate both event detection and risk ranking when grid decisions depend on predicted constraint violations [24]. Suitable metrics include RMSE for loading ratio, voltage mean absolute error, F1-score for congestion classification, area under the precision-recall curve, and expected calibration error. These metrics should be reported separately for normal, stressed, and topology-changed operating conditions.

Validation strategy

A rigorous validation strategy should test temporal generalization, topology generalization, and DER-penetration sensitivity without claiming that these tests have already been performed. Multi-area distribution state-estimation work shows that models can face different observability and coupling conditions across feeder regions [25]. Therefore, future validation should include chronological splits, unseen switching configurations, high-PV days, high-EV-loading evenings, and flexibility-scarcity scenarios. Such validation would determine whether the conceptual PINN-GNN is robust enough for operational screening.

Benchmarking

Data-driven GNN without physics

The first benchmark is a data-driven GNN that uses the same graph, node features, and edge features but removes physics-informed loss terms. This benchmark isolates the value of power-balance, voltage, and thermal-limit regularization, following the logic of comparing physics-aware and unconstrained neural estimators [1]. If implemented, the comparison would show whether physical penalties improve out-of-distribution behavior under switching events and rare congestion states. The benchmark is especially important because a graph architecture alone does not guarantee physically feasible predictions.

LSTM and temporal baselines

The second benchmark class consists of LSTM or gated temporal models that use bus-level time series but do not explicitly represent feeder topology. Spatial-temporal residential load forecasting research shows that temporal learning is valuable, but graph structure can add information beyond sequence modeling alone [15]. A topology-free LSTM baseline would therefore test whether congestion forecasting can be solved from temporal patterns alone or requires electrical adjacency. The conceptual expectation is that LSTMs may perform adequately for recurring load patterns but struggle with localized congestion caused by topology or DER-location effects.

Persistence forecast

The third benchmark is a persistence model that assumes future loading and voltage risk follow the most recent observed operating condition. Persistence is operationally simple and can be surprisingly competitive for slowly varying states, but it cannot anticipate weather-driven PV ramps, EV charging waves, or scheduled topology changes. Gated spatial-temporal graph forecasting studies demonstrate the importance of modeling changing wide-area bus conditions rather than assuming static continuation [22]. Persistence is included as a transparent lower bound against which the value of topology, physics, and flexibility inputs can be judged.

Explainability

GNNexplainer and attention visualization

The proposed explainability layer combines edge-attention visualization with graph attribution methods to identify which lines, buses, and DER flexibility features drive a congestion forecast. General explainability surveys for graph neural networks support the use of subgraph and feature attribution when model decisions depend on relational structure [10]. Attention weights can indicate which electrical paths were emphasized during message passing, while GNNExplainer-style masks can identify compact feeder subgraphs associated with predicted overloads. These outputs would be used as diagnostic aids rather than as formal proofs of causality.

Physically relevant feature importance

For operator trust, explanation outputs should align with physical intuition, such as highlighting downstream PV export during voltage rise or upstream transformer limits during EV charging peaks. Explainable power-grid fault detection research illustrates how graph explanations can support interpretation of network-level events [26]. In the proposed framework, feature importance should distinguish between baseline injections, flexibility headroom, topology status, and equipment ratings. Physically coherent explanations would strengthen confidence that the PINN-GNN has learned meaningful feeder relationships rather than spurious correlations.

Operator-usable insights

The purpose of explainability is to convert a congestion probability into actionable operational insight. Explainable multi-fidelity neural estimation research shows that uncertainty-aware and interpretable learning can help operators understand why a distribution-state prediction changes [27]. In the proposed model, an explanation may show that a forecasted overload depends on limited battery headroom at a downstream node, an open tie switch, and high PV export on a lateral. Such explanations could guide flexibility activation, topology review, or closer monitoring before a congestion event materializes.

Figure 2 shows how probabilistic congestion forecasts are translated into physically interpretable operator insights by linking predicted violations to influential feeder subgraphs, DER flexibility conditions, topology status, and equipment constraints.

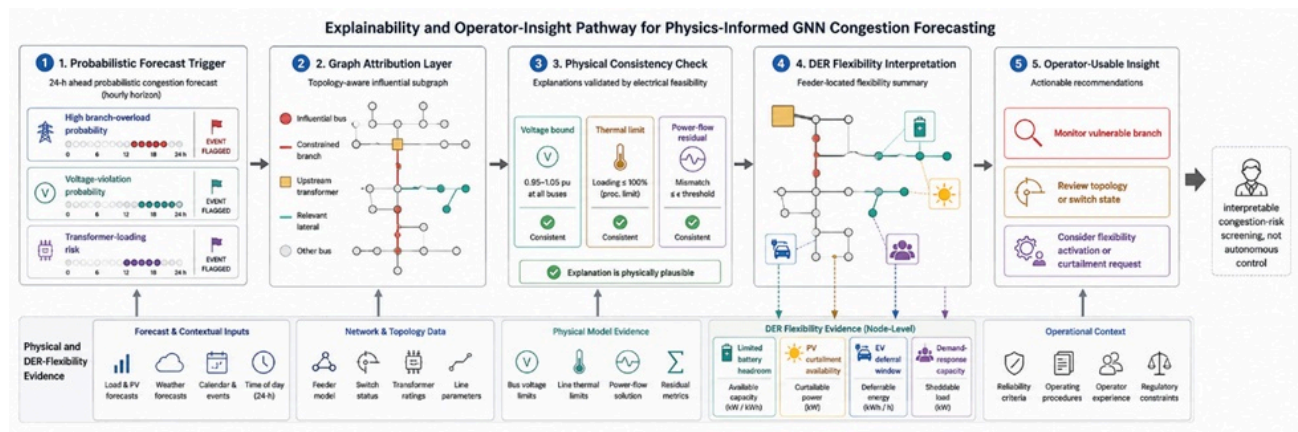


Figure 2. Explainable Congestion-Risk Interpretation and Operational Use of PINN-GNN Forecasts

Conceptual Results and Expected Evaluation Outcomes

Expected congestion detection behavior

As a conceptual paper, this article does not report measured RMSE, F1-score, calibration error, or experimental feeder results. Instead, it specifies the expected evaluation behavior that should be tested in future work. Physics-informed voltage prediction and graph-based state-estimation studies suggest that combining topology with physical residuals should improve rare-event detection and reduce infeasible forecasts [9]. The main expected advantage of the PINN-GNN is not merely higher accuracy but more reliable congestion screening under DER variability and topology changes.

Expected calibration and reliability

The proposed probabilistic output should be evaluated for calibration because operators need meaningful risk probabilities rather than only ranked alarms. Graph-based operational risk assessment emphasizes that decision support depends on whether predicted risk levels correspond to actual violation likelihood [24]. In future experiments, calibration should be tested across normal conditions, high-PV intervals, EV evening peaks, and contingency-like topology states. A physics-informed model is expected to reduce overconfident false alarms by penalizing predictions that imply physically inconsistent flows or voltages.

Conceptual ablation on physics-informed components

A future ablation study should remove physics-informed terms one at a time to identify which constraints contribute most to feasible congestion forecasts. Line-parameter learning with physics-informed graphical methods demonstrates that graph-structured physical constraints can improve inference of electrical quantities [28]. Removing the power-balance

penalty would test nodal consistency, removing voltage-bound penalties would test voltage-risk realism, and removing thermal-limit penalties would test overload sharpness. This ablation is essential because overly strong physics penalties may also reduce flexibility when approximation errors exist.

Sensitivity to der flexibility data quality

The framework should also be tested under degraded flexibility inputs, including biased PV curtailment estimates, uncertain EV availability, and inaccurate battery state-of-charge ranges. Renewable flexibility research indicates that system operation depends not only on nominal capacity but also on the reliability of available flexibility forecasts [29]. Sensitivity analysis should compare perfect, noisy, delayed, and missing flexibility signals to determine how robust the model is when DER observability is imperfect. Table 3 presents the proposed conceptual benchmarking matrix and the expected comparative behavior without reporting experimental numbers.

Table 3. Conceptual Benchmarking Matrix and Expected Comparative Behavior of Models and Ablations

Model or ablation	Physics-informed constraints	Topology-aware graph representation	DER flexibility inputs	Expected strength	Expected weakness
Proposed PINN-GNN	Included through power-balance, voltage, and thermal penalties	Included through active graph and edge-conditioned message passing	Included as node-level forward-looking features	Most coherent framework for risk-aware, topology-sensitive congestion forecasting	Requires high-quality topology and flexibility inputs
Data-driven GNN	Not included	Included	Included	Learns spatial congestion patterns and DER-location effects	May produce physically inconsistent voltage or loading forecasts
PINN-GNN without flexibility	Included	Included	Excluded	Tests value of physical regularization alone	Cannot anticipate mitigation or risk changes caused by available DER flexibility
PINN-GNN without topology updates	Included	Fixed or simplified adjacency	Included	Tests value of physics and flexibility under static topology	May fail during reconfiguration or backfeeding events
LSTM temporal model	Not included	Excluded	Can be included as time-series features	Captures recurring temporal load and PV patterns	Weak representation of feeder adjacency and localized constraints
Persistence model	Not included	Excluded	Excluded	Transparent operational lower bound	Cannot anticipate ramps, topology changes, or flexibility-driven risk shifts

Conclusion

This conceptual article proposed a physics-informed graph neural network framework for distribution-grid congestion forecasting with topology-aware DER flexibility signals. The framework represents buses as nodes, lines and transformers as edges, and flexible DER availability as forward-looking node features. It is designed to forecast hourly line congestion and voltage-violation probabilities over a 24-hour horizon.

The central strength of the proposed framework is its integration of graph topology, physical consistency, and flexibility awareness. Instead of treating congestion forecasting as a purely statistical time-series problem, the model embeds feeder structure and physical operating limits directly into the learning design. This makes the framework suitable for future applications in proactive distribution operation, flexibility screening, and risk-aware planning.

Because the paper is conceptual, it does not claim experimental performance, measured accuracy, or validated superiority over baselines. Instead, it provides the model structure, data requirements, loss formulation, benchmarking design, and explainability workflow needed for future empirical studies. This distinction is important because it keeps the contribution rigorous without implying that unavailable experiments were conducted.

Future work should implement the framework on realistic feeder datasets, compare it against graph and temporal baselines, and evaluate its robustness under topology changes, high DER penetration, and imperfect flexibility forecasts. Further development should also connect the forecasting layer with real-time DER control and market-based flexibility activation. The proposed PINN-GNN can then be tested not only as a predictor of congestion but also as a decision-support component for active distribution-grid operation.

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