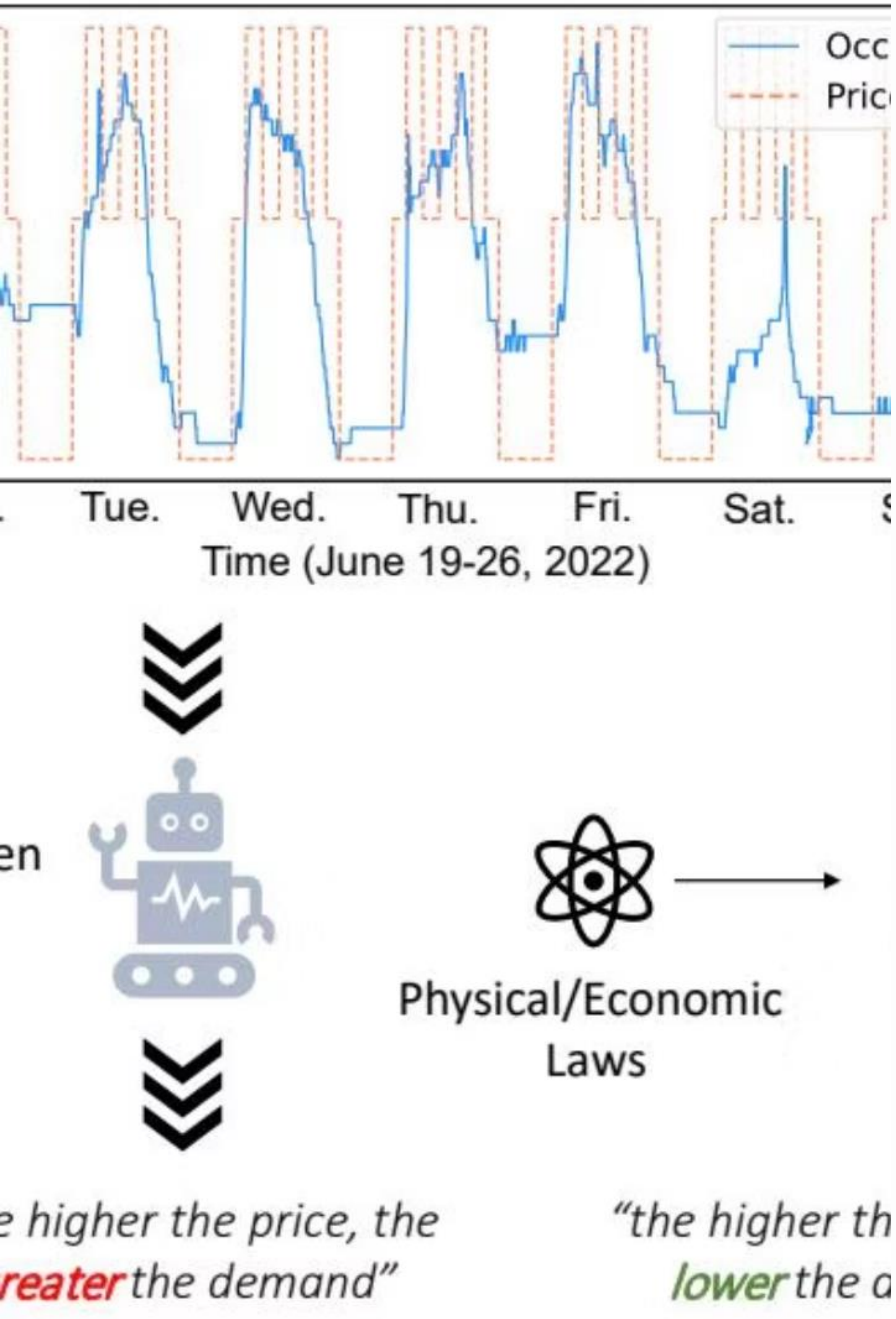


A Physics-Informed and Attention-Based Graph Learning Approach for Regional EV Charging Demand Prediction

This presentation introduces PAG, a novel model combining graph and temporal attention mechanisms with physics-informed meta-learning to predict electric vehicle (EV) charging demand accurately and interpretably. The approach addresses challenges in spatiotemporal feature extraction and misinterpretations caused by price fluctuations.

Evaluated on a dataset of 18,061 EV charging piles in Shenzhen, China, PAG achieves state-of-the-art forecasting performance and correctly interprets adaptive demand changes due to pricing.

Challenges in EV Charging Demand Prediction

Feature Extraction

EV charging stations are spatially distributed and interrelated. Capturing hidden temporal and spatial patterns in high-dimensional, heterogeneous data is critical for accurate demand prediction.

Biased Information

Data-driven models often misinterpret the relationship between price and demand, e.g., higher prices mistakenly linked to higher demand due to biased observed data.

Knowledge Learning

Demand-price relationships vary across time and locations. A unified, scalable method is needed to fairly learn from observed and physics-informed tuning samples.

Related Solutions and Limitations

Graph and Temporal Models

Integration of Graph Neural Networks (GNNs) and Recurrent Neural Networks (RNNs) improves spatiotemporal prediction but suffers from inflexible weight assignment.

Attention Mechanisms

Attention-based models enhance feature representation but lack integration to capture interactions among EV charging factors fully.

Physics-Informed and Meta-Learning

Physics-Informed Neural Networks (PINNs) and meta-learning help address misinterpretations but face challenges in knowledge learning and data acquisition.

Proposed Approach: PAG Architecture

Graph Embedding Module

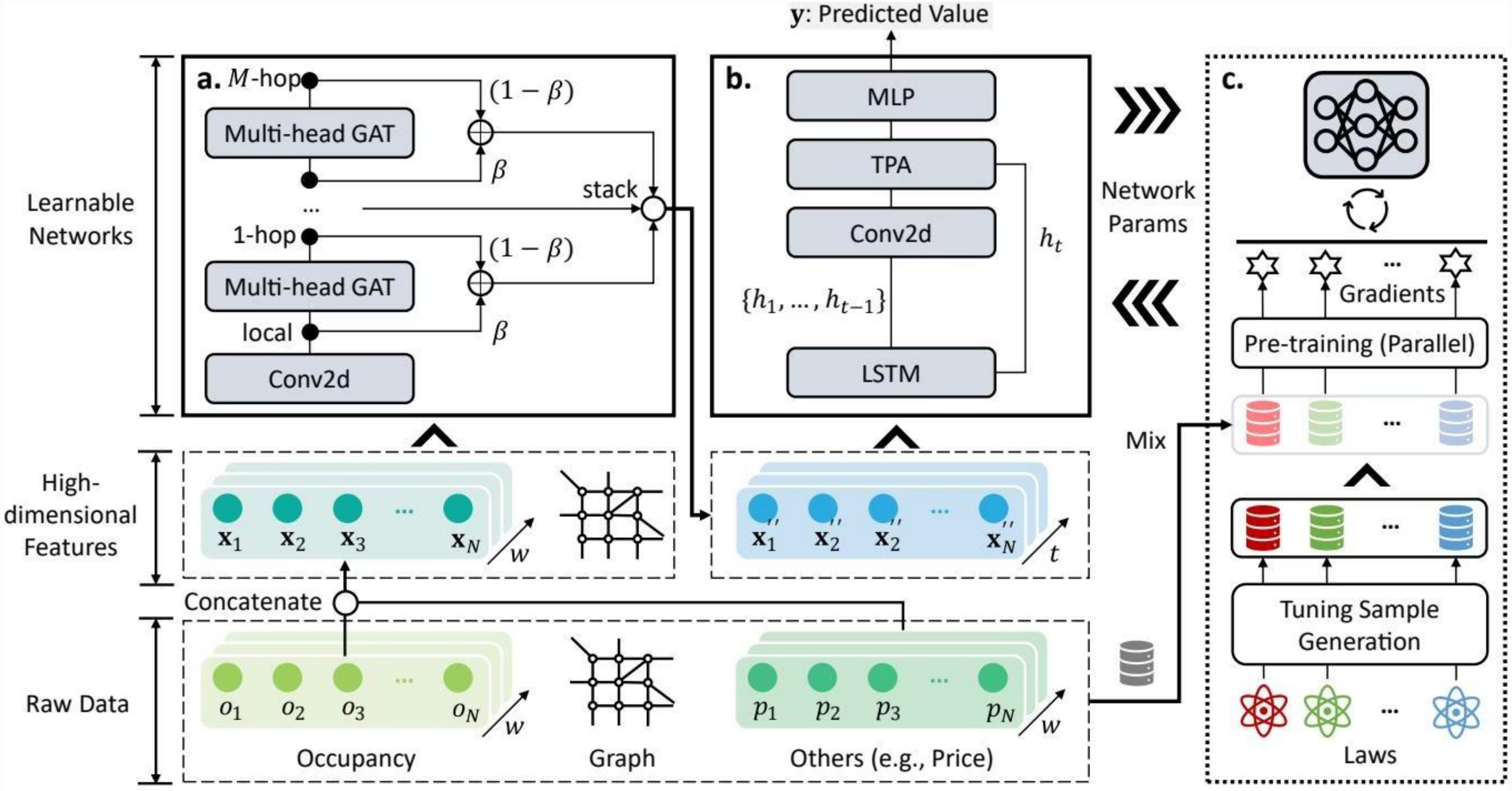
Uses Graph Attention Network (GAT) with masked multi-head attention to capture spatial relationships among urban zones.

Multivariate Decoder Module

Employs Temporal Pattern Attention (TPA) combined with LSTM to decode multivariate time series for demand prediction.

Model Pre-training Module

Applies physics-informed meta-learning (PIML) with law-based pseudo-sampling to avoid misinterpretations during training.



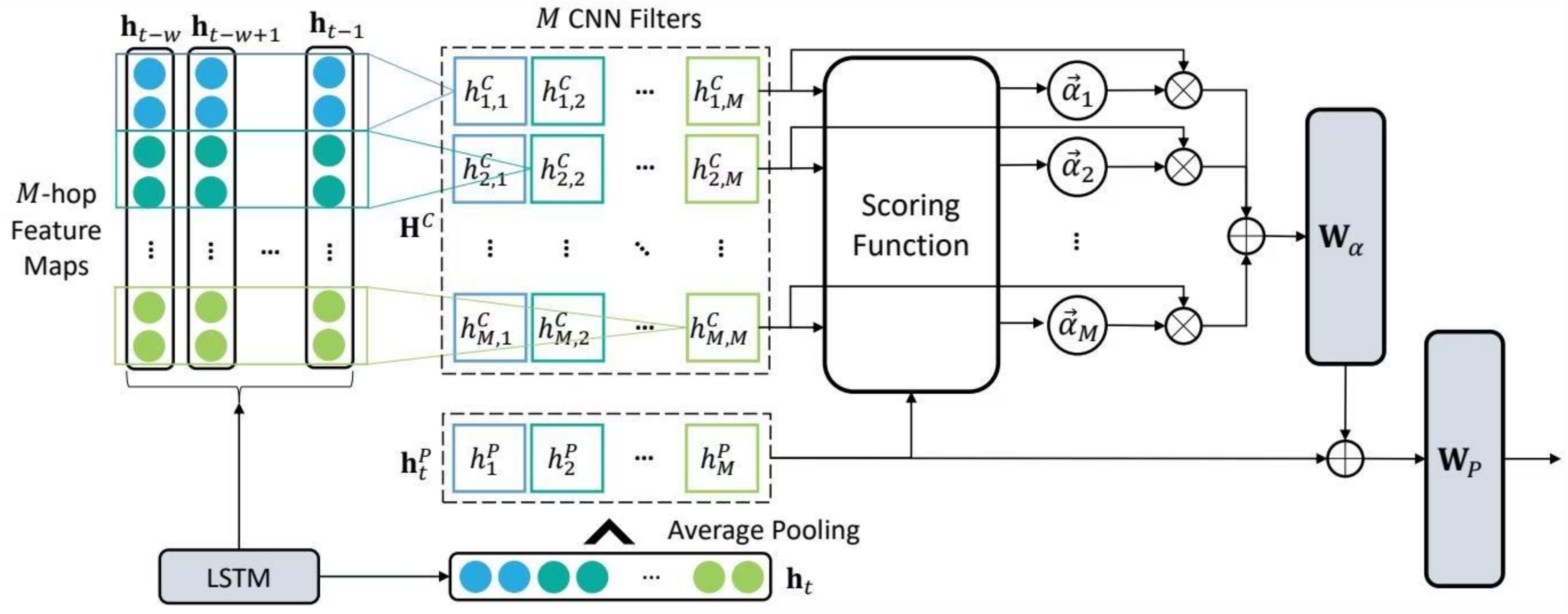
Graph Embedding and Temporal Decoding Details

Graph Embedding

GAT calculates attention coefficients between nodes to weigh neighbor features, propagating spatial information through multiple layers with residual connections to prevent over-smoothing.

Temporal Decoder

TPA-LSTM extracts temporal patterns via LSTM gates and applies convolution and pooling to generate attention scores, integrating hop-wise and sequence-wise features for prediction.



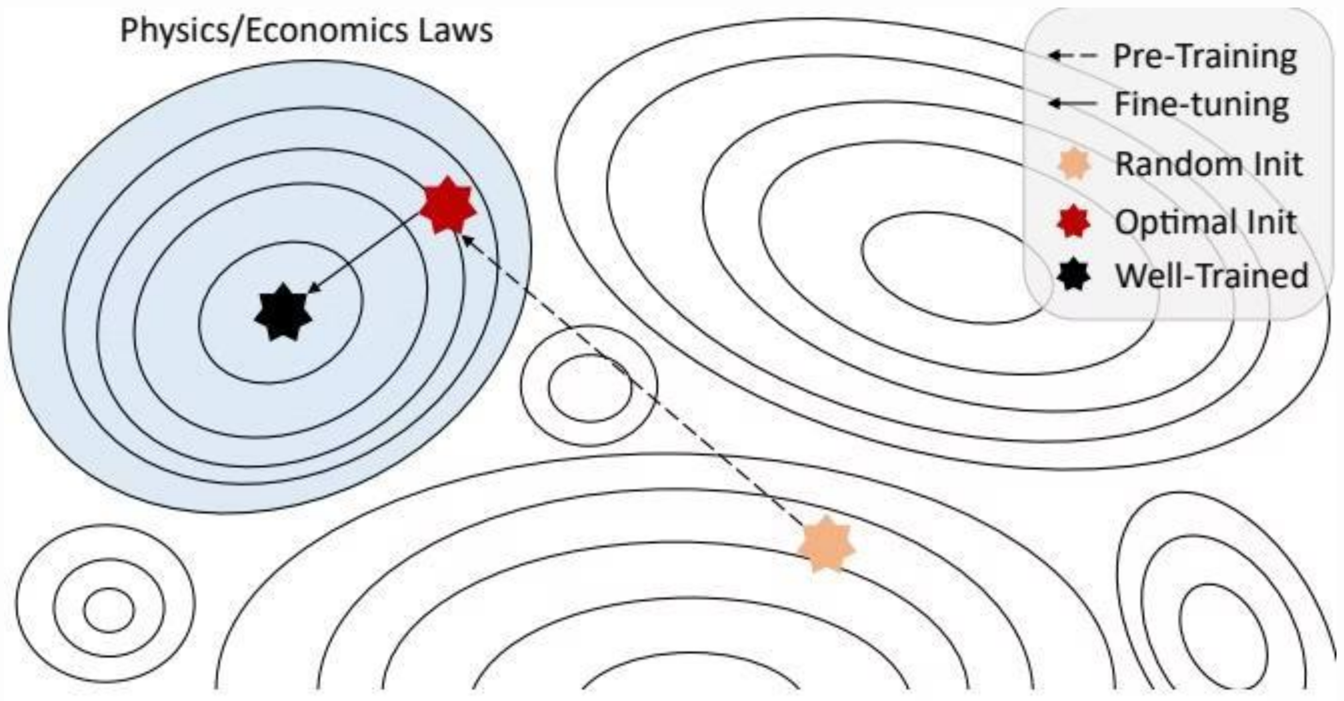
Physics-Informed Meta-Learning Pre-training

Motivation

Pre-training with tuning samples generated from physical and economic laws helps the model avoid local optima that cause misinterpretations, such as wrongly associating higher prices with higher demand.

Methodology

Uses First-order Model-agnostic Meta-learning (FO-MAML) to optimize initial parameters by combining tuning and observed samples, gradually reducing tuning sample proportion during training.



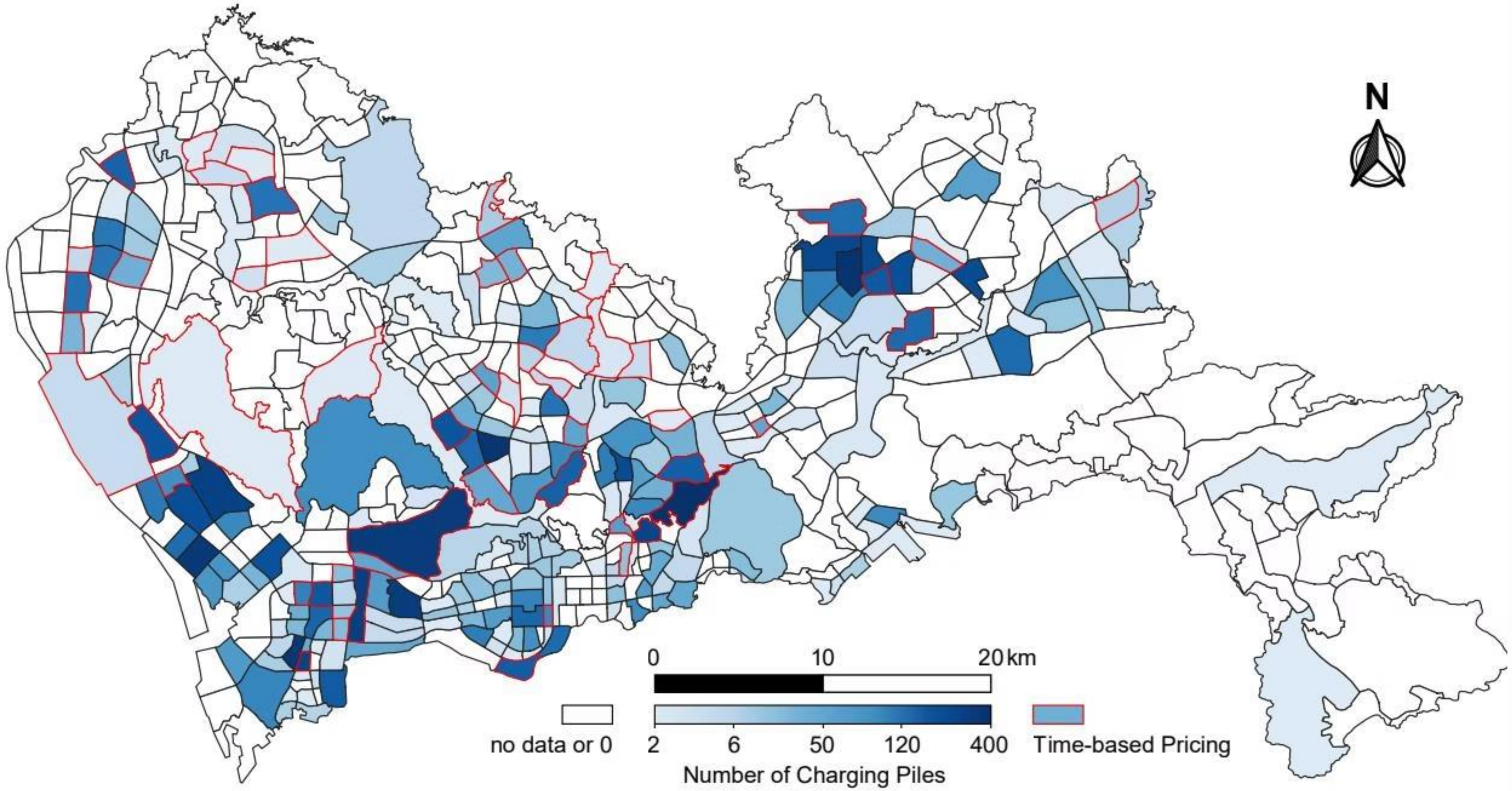
Evaluation Setup and Dataset

Dataset

Data from 18,061 EV charging piles in Shenzhen over 30 days, organized into 247 traffic zones forming a graph with 1006 edges. Pricing schemes include time-based and fixed pricing.

Experimental Settings

Window size of 12 intervals (60 minutes), 2 GAT layers, 4 attention heads, residual coefficient 0.5, and Adam optimizer with learning rate 0.001. Pre-training epochs: 200; fine-tuning epochs: 1000.



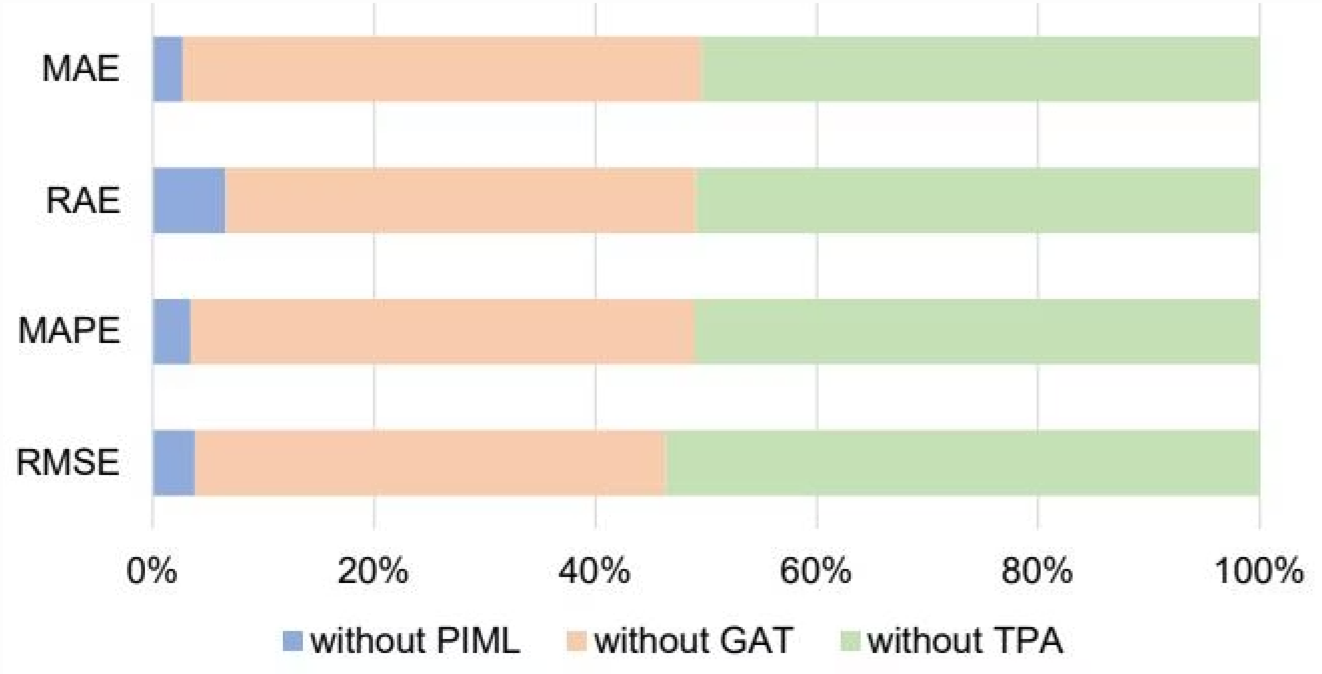
Performance and Ablation Results

Forecasting Accuracy

PAG outperforms baselines including VAR, LSTM, GCN-LSTM, and AST-GAT with 6.57% average error reduction across RMSE, MAPE, RAE, and MAE metrics.

Ablation Study

Removing TPA or GAT modules significantly degrades performance, confirming their critical roles. Pre-training (PIML) reduces misinterpretation effects and improves accuracy marginally.



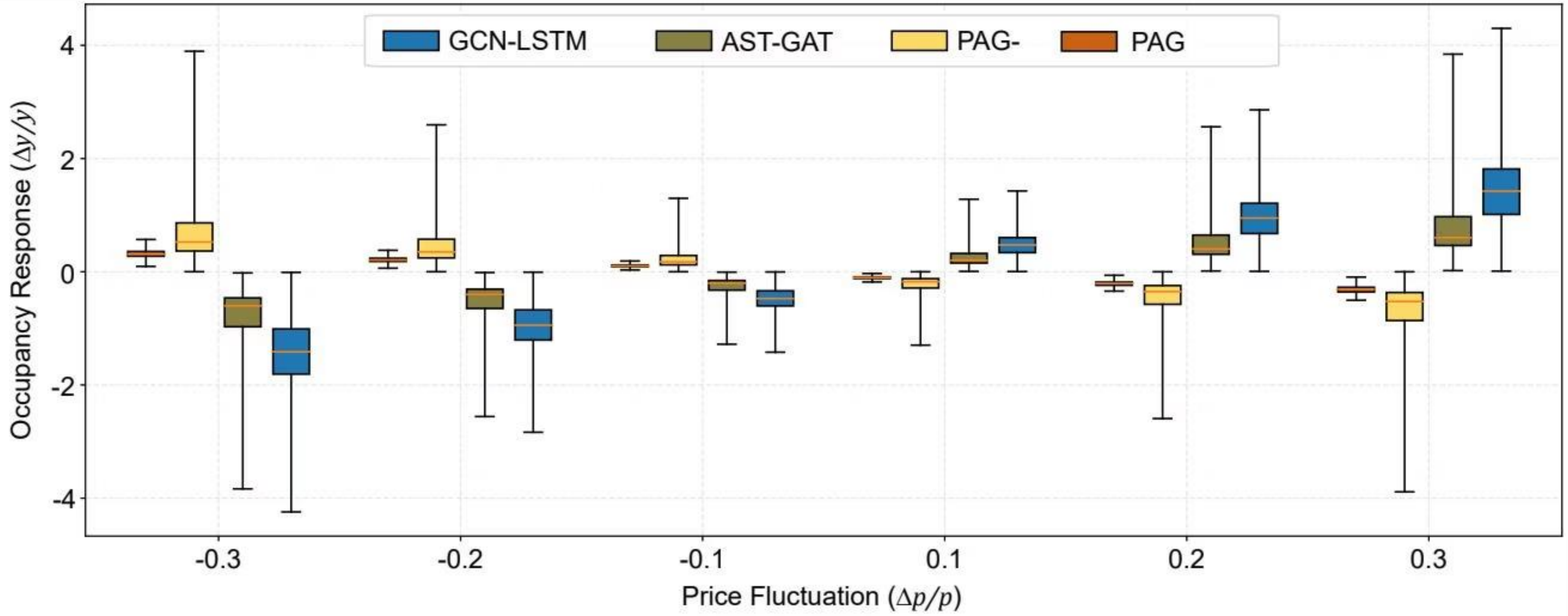
Model Interpretation and Conclusions

Interpretation of Price Effects

PAG correctly models inelastic EV charging demand to price fluctuations and captures spillover effects, where price increases reduce local demand but increase demand in 1-hop neighboring zones.

Conclusions and Future Work

PAG advances EV charging demand prediction by integrating attention mechanisms and physics-informed meta-learning. Future work includes expanding misinterpretation corrections, automating critique modules, and quantifying spillover effects for policy optimization.



Key Takeaways and Future Outlook

Novel Architecture

PAG combines attention and physics-informed meta-learning to address prediction gaps.

Proven Performance

Significant accuracy gains confirmed by robust error reduction across metrics.

Future Insights

Offers powerful tools for urban planning and policy optimization.

Graph Attention Network (GAT) for Spatial Embedding

Attention Computation

GAT calculates attention coefficients between nodes. This assigns varying importance to neighboring features, crucial for spatial embedding.

Multi-Head & Residual

Multiple attention heads capture diverse relationships. Residual connections enhance information flow, ensuring stable and robust learning in complex graphs.

Feature Propagation

Neighborhood features propagate across the graph. GAT dynamically aggregates information based on learned attention, refining node representations.

Temporal Pattern Attention Decoder (TPA-LSTM)

LSTM Cell Gates

The LSTM cells manage information flow using gates. These equations define input, forget, and output processes. They ensure relevant data is retained or discarded.

Temporal Attention Scoring

Attention scores weigh past hidden states. This mechanism identifies crucial temporal patterns. It assigns varying importance to different time steps.

Integrated Attention

Hop-wise and sequence-wise attention integrate. This captures both local and global temporal dependencies. It enhances the decoder's predictive power.

Physics-Informed Meta-Learning Pre-training

Addressing Model Flaws

PIML overcomes local optima and misinterpretation. It enhances prediction robustness.

Law-Based Data

It generates synthetic samples using price elasticity. This ensures physical consistency in data.

Meta-Learning Goal

This formulates objectives for optimal parameter initialization. It guides efficient model learning.

Pre-training Process

The algorithm integrates an adaptive training loop. It optimizes initial model parameters effectively.

Experimental Setup and Dataset

- **Spatial Graph:** The dataset comprises 247 traffic zones in Shenzhen. It includes detailed information on 18,061 charging piles.
- **Temporal Data:** Hourly EV charging demand is captured for 2019 and 2020. This data is split for robust training and evaluation.
- **Pricing Schema:** The dataset features varying pricing models. Both time-based and fixed rate structures are analyzed.

Experimental Configuration and Baselines (Table I)

Hyperparameters & Optimization

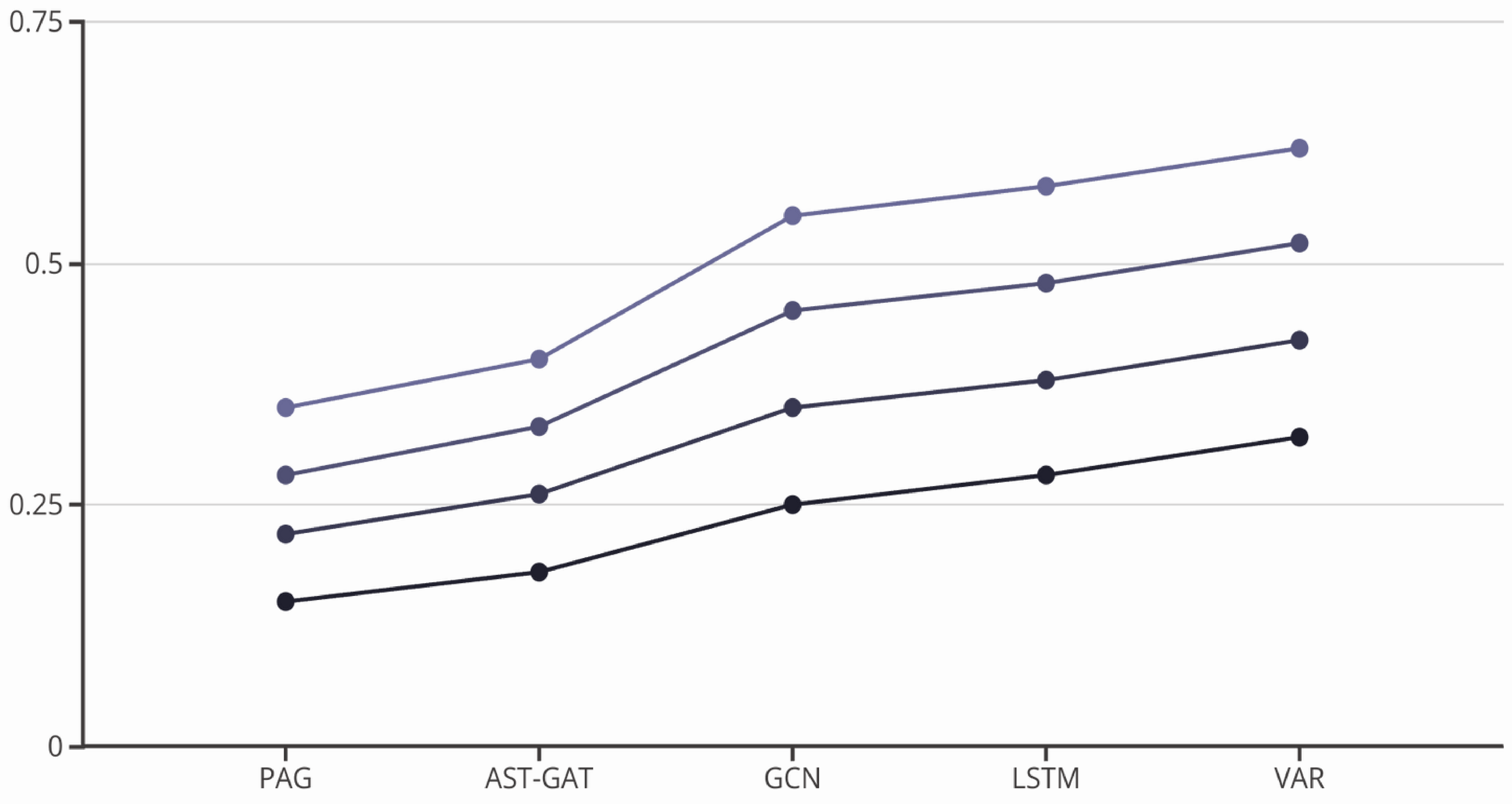
PAG and baseline models underwent rigorous hyperparameter tuning. An Adam optimizer minimized loss effectively.

Evaluation Metrics

Performance was assessed using MAE, RMSE, and MAPE. These metrics quantified prediction accuracy against established baselines.

Quantitative Prediction Performance

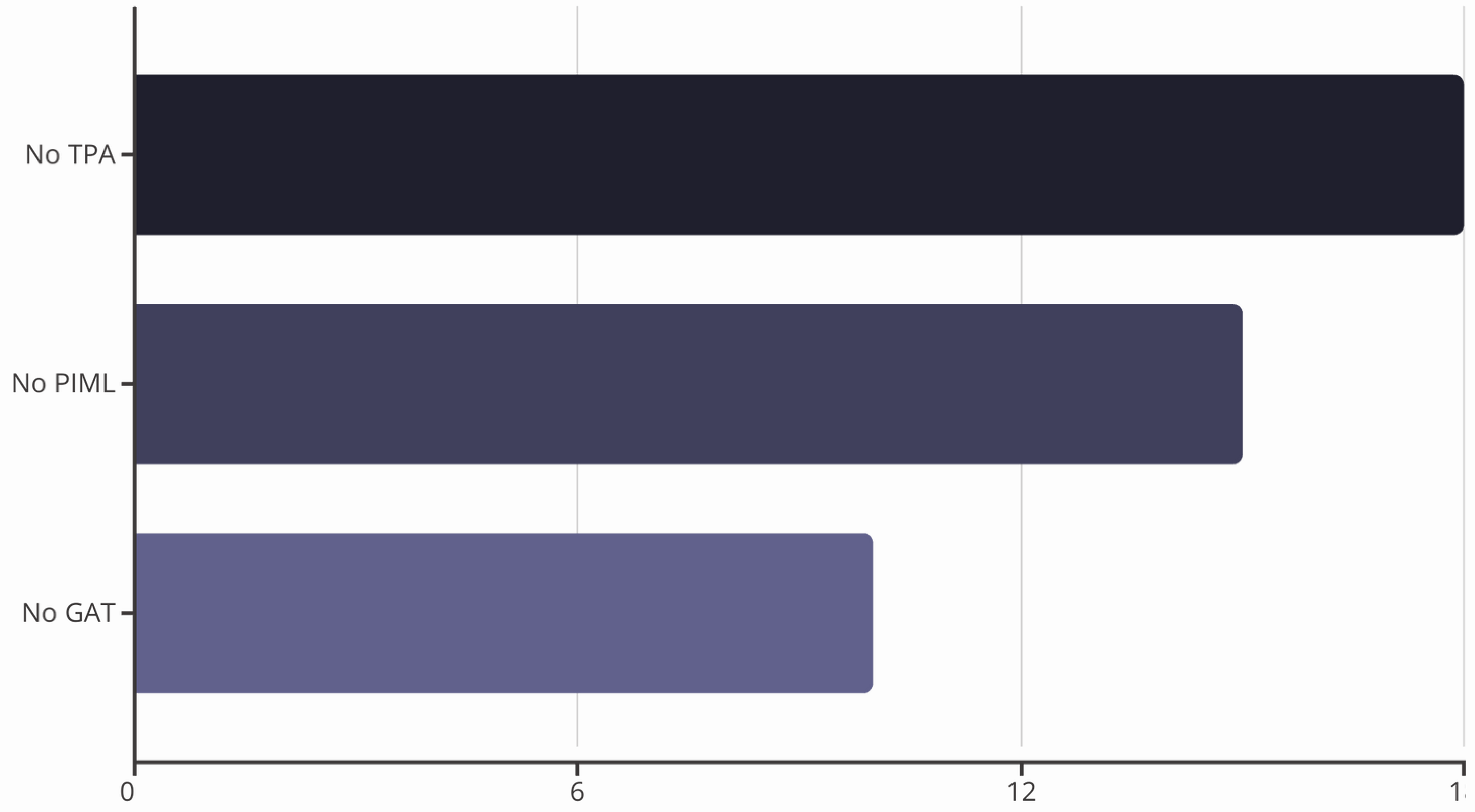
We rigorously evaluated the PAG model against established baselines. This chart illustrates the Root Mean Square Error (RMSE) across various forecasting intervals, highlighting model accuracy.



PAG consistently demonstrates superior performance across all prediction intervals. Its unique architecture effectively minimizes forecasting errors. This validates the strength of its integrated spatial and temporal learning capabilities

Ablation Study: Component Impact

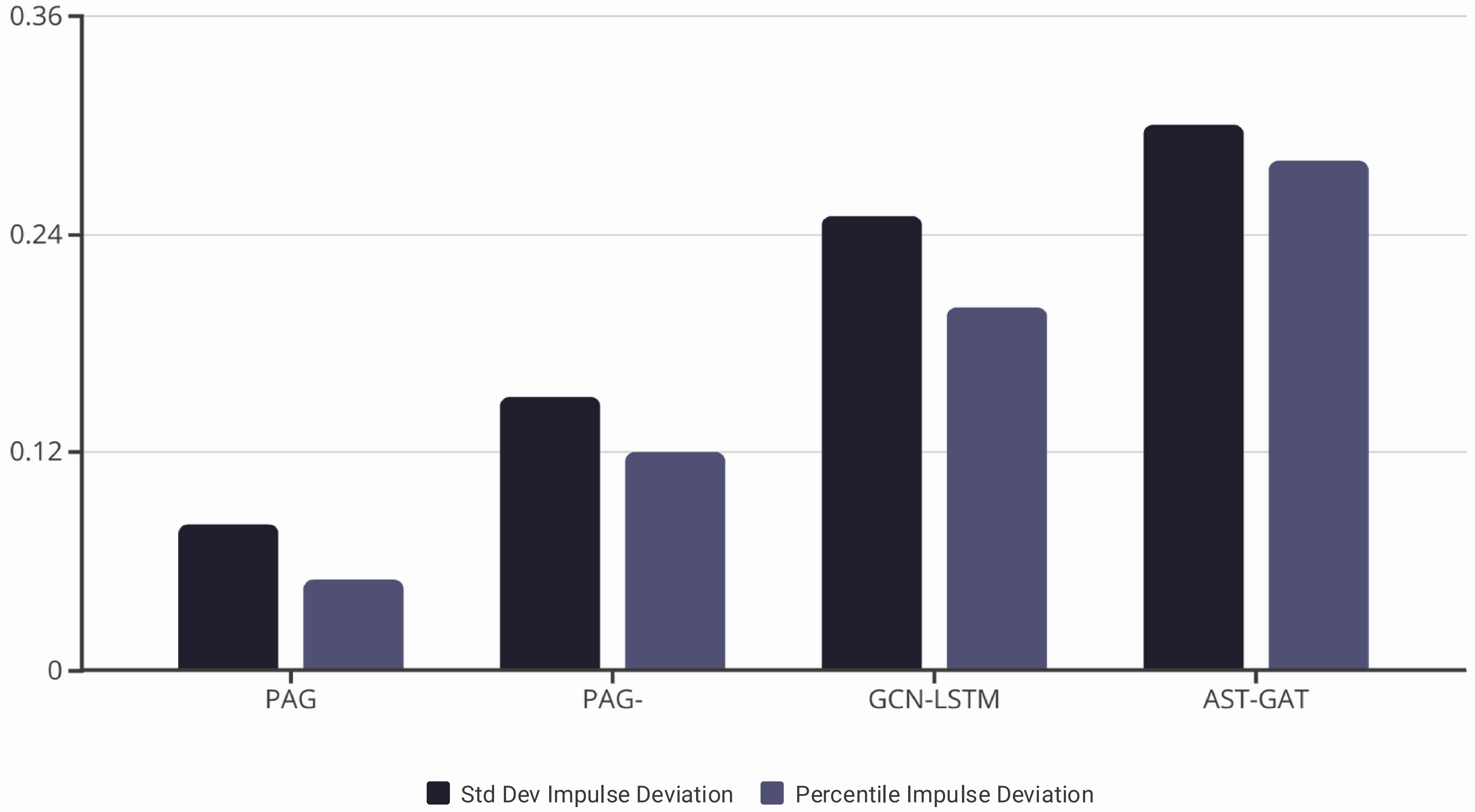
Conducted an ablation study to quantify the contribution of each core component of the PAG model. This analysis reveals how removing specific modules affects overall prediction accuracy.



The results show that the Temporal Pattern Attention Decoder (TPA) has the most significant impact. Each module plays a vital role in the PAG model's superior performance

Interpretation of Price-Demand Relationship

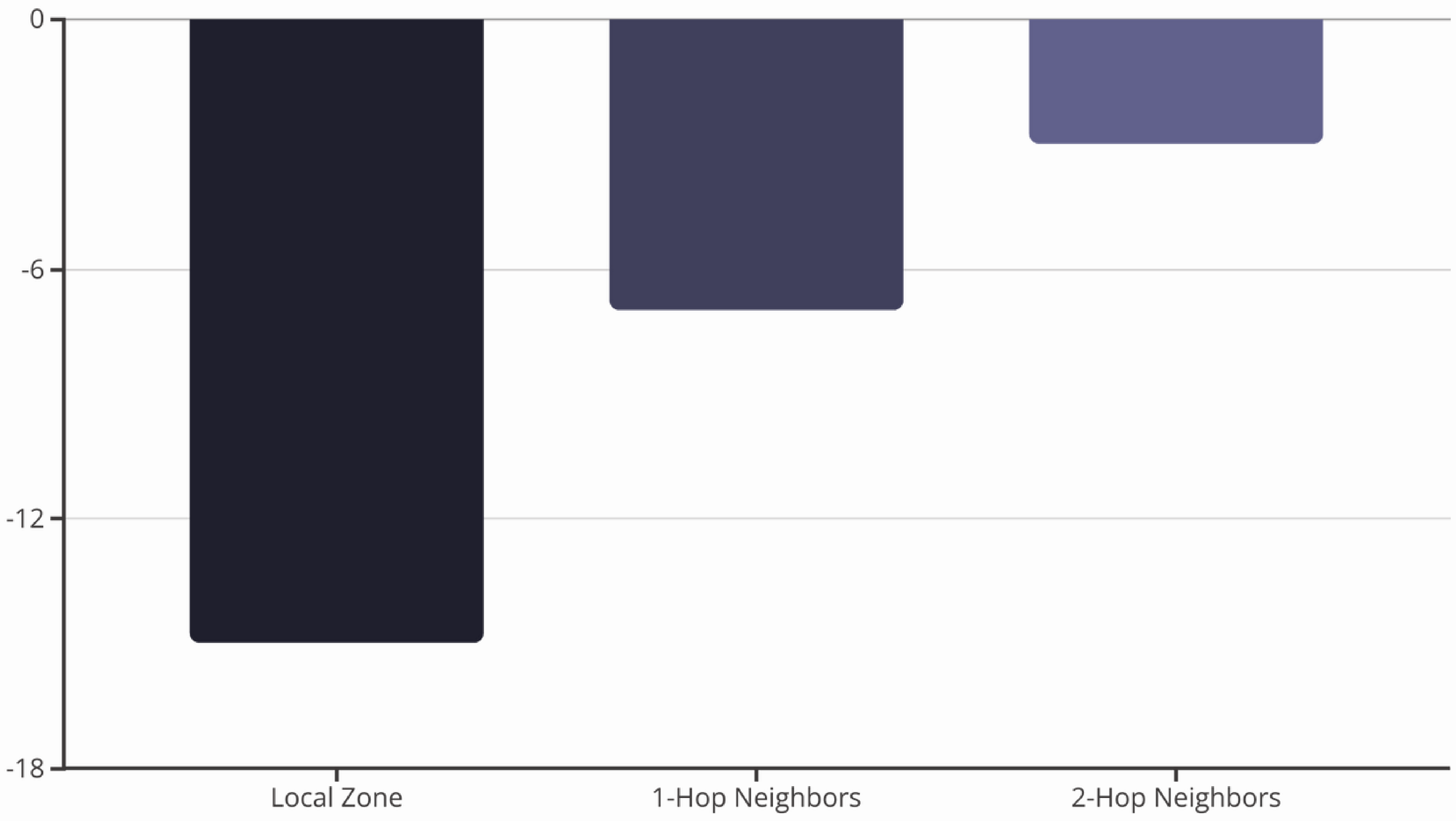
This analysis reveals how different models interpret price impacts on EV charging demand. Assessed their prediction deviation under specific price impulses. Lower deviation indicates better model interpretability.



PAG consistently demonstrates superior understanding of the price-demand relationship. It accurately captures how demand responds to various pricing strategies

Spillover Effect Analysis

Analyzed the "spillover effect," examining how local price changes influence demand in neighboring zones. This chart illustrates the predicted demand response across different spatial distances.



The analysis reveals that demand shifts significantly in the immediate vicinity. The impact diminishes as distance from the price fluctuation increases

Sensitivity Analysis

Sample Distribution & Parametric Choices

Tuning sample distributions and selecting optimal parameters significantly impacts model robustness. This ensures the PAG model generalizes well to varied data patterns.

Pre-training Epochs & Learning Rates

The number of pre-training epochs and chosen learning rates are critical. These settings influence model convergence and overall prediction accuracy for the meta-learning phase.

Visualization of Model Attention

Model's attention mechanisms reveal its focus. Graph Attention Networks (GAT) prioritize critical neighboring zones. Temporal Pattern Attention (TPA) highlights key historical time steps.

This selective focus enhances prediction accuracy. It ensures robust learning from complex spatial-temporal data.

Theoretical Discussion on Meta-Learning and Physics Integration

Discussion of integrating meta-learning with physical laws. This enhances model performance.

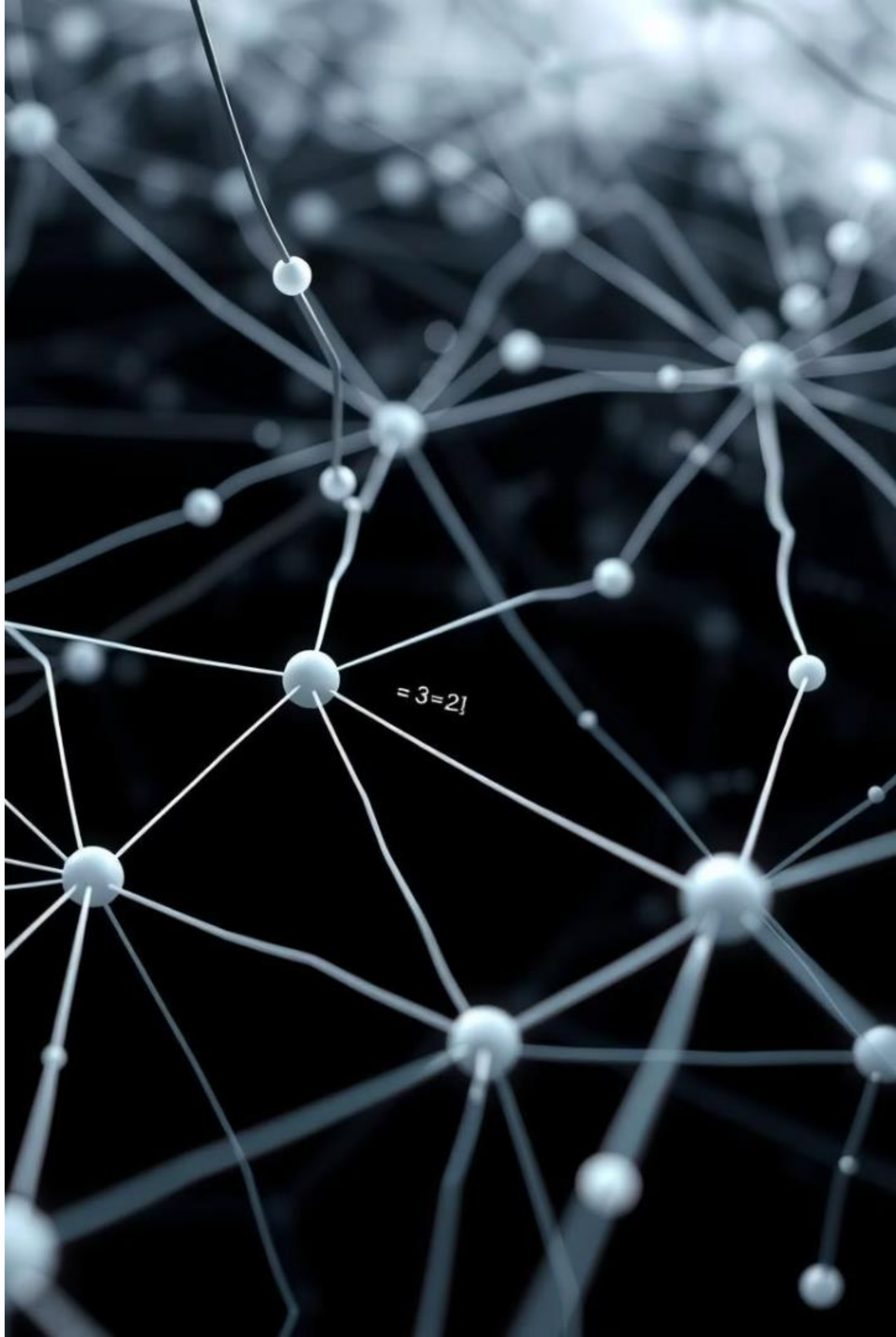
Key Advantages

It boosts robustness and generalization. The model learns with less data.

Implementation Hurdles

Integration adds complexity. It demands careful validation with noisy real-world data.

This approach offers promising extensions to other ITS applications. Think traffic flow and smart city infrastructure.



Key Limitations and Future Directions

Enhanced Interpretability

Address additional types of misinterpretations to improve model understanding.

Automated Tuning

Develop automated tuning for hyperparameters and pre-training schedules.

Explicit Spillover Quantification

Quantify spillover effect strength more explicitly for better insights.

Paper Summary

PAG model integrates physics-informed meta-learning with attention-based graph networks. It offers robust, generalizable EV charging demand prediction.

PAG Model Overview

This novel approach combines graph learning, attention mechanisms, and physical laws for enhanced prediction.

Validation and Insights

Experiments confirm superior performance and interpretability. We revealed critical insights into the price-demand spillover effect.

Key Takeaways and Future Outlook

- PAG enables intelligent EV infrastructure management and optimized pricing policies.
- Expand physics-informed models to multi-modal transport data for broader applications.
- Develop reinforcement learning for adaptive, dynamic EV charging pricing strategies.
- Implement scalable, real-time PAG deployment in complex urban ITS environments.

Appendix

- **Key Formulas Summary:** Review the main equations for PAG, including GAT, TPA, and Physics-Informed Meta-Learning.
- **References:** Access a comprehensive list of all critical sources cited in the research paper.

Experimental Configuration and Baselines

Established a robust experimental setup. This included defining key parameters and baseline models. This approach allows for clear performance comparisons.

Model	Approach	Key Characteristics
ARIMA	Statistical	Time-series forecasting method.
SVR	Machine Learning	Non-linear regression capabilities.
GRU	Deep Learning	Handles sequential data dependencies.
GCN	Graph Neural Network	Captures spatial correlations on graphs.
PAG (Ours)	Hybrid	Integrates physics-informed meta-learning.

Thank you for your time and patience.

appreciate your engagement and thoughtful questions.
now open for discussion. Your feedback is valuable.

Connect for further details or collaborations.