Hierarchical Graph Convolutional Networks with Attention Mechanisms for Integrated Urban Traffic and Energy Network Prediction Using UAV and GIS Data

Noreen Fatima[1], Amna Shahid[1]
[1]Government College University, Lahore
*Correspondence:noor.fatima@gmail.com

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Urbanization and the rapid growth of both vehicular traffic and energy demand present significant challenges for sustainable urban planning. Accurate spatiotemporal modeling of traffic flow and energy network infrastructure is crucial for efficient management, real-time decision-making, and smart city development. This study proposes a hierarchical Graph Convolutional Network (GCN) integrated with attention mechanisms to model complex interactions within large-scale urban traffic and energy systems. High-resolution data collected from unmanned aerial vehicles (UAVs) and GIS-based spatial datasets were used to construct predictive models for traffic congestion and energy network behavior. The proposed framework captures local and global dependencies, prioritizes critical nodes, and efficiently manages large-scale interconnected systems. Results demonstrate high predictive accuracy in traffic flow (MAE = 3.12 vehicles/min, Pearson r = 0.91) and energy network node classification (accuracy = 95.3%). Sensitivity and ablation analyses confirm the importance of hierarchical decomposition and attention mechanisms for model performance. Case studies illustrate the practical utility of the framework in real-time traffic management and predictive energy infrastructure monitoring. Overall, this research presents a scalable, robust, and data-driven methodology for integrated urban system modeling, supporting informed decision-making and sustainable infrastructure planning.

Keywords: Urban Traffic Prediction, Energy Network Modeling, Spatiotemporal Analysis

Introduction:

The integration of renewable energy sources into power grids necessitates the development of advanced methodologies for modeling and managing the spatial and temporal dynamics of electricity networks. Traditional approaches often fall short in capturing the complex interdependencies inherent in modern grid infrastructures. Recent advancements in Graph Neural Networks GNNs) have shown promise in addressing these challenges by effectively modeling the topological and temporal aspects of power systems. For instance, the PowerGNN framework combines [1] GraphSAGE convolutions with [2] Gated Recurrent Units (GRUs) to predict power system states under high renewable integration, achieving significant improvements in predictive accuracy.

Similarly, in the realm of traffic prediction, the emergence of Spatio-Temporal Graph Neural Networks[3] (STGNNs) has revolutionized the field. These models adeptly capture both spatial dependencies, such as road network structures, and temporal dynamics, like traffic flow variations over time. The integration of attention mechanisms further enhances their capability to focus on critical temporal and spatial features, leading to more accurate traffic forecasts.

Despite these advancements, challenges persist in scaling these models to handle large, complex networks and in integrating diverse data sources effectively. Addressing these challenges is crucial for the development of robust predictive models that can support the efficient operation and planning of power grids and urban transportation systems.

Research Gap:

While GNNs have demonstrated efficacy in modeling power grid and traffic systems, several gaps remain in the literature. Existing studies often focus on specific components of the grid or operate under simplified assumptions that may not fully represent the complexities of real-world systems. Moreover, the scalability of GNN models remains a concern, especially when dealing with large-scale grids that encompass diverse geographical and infrastructural variations.

Additionally, there is a need for comprehensive frameworks that integrate geospatial data with GNNs to enhance the accuracy and applicability of predictive models across different regions and grid configurations. Such integration can provide a more holistic understanding of the systems, facilitating better decision-making and planning.

Furthermore, the incorporation of attention mechanisms within GNNs has been explored in various contexts, but their application in large-scale power grid and traffic systems remains under-explored. Attention mechanisms can potentially improve model performance by allowing the network to focus on the most relevant parts of the input data, thereby enhancing prediction accuracy.

Objectives:

This research aims to develop an advanced GNN-based framework that incorporates both geospatial and temporal data to model power grid and traffic system dynamics comprehensively. The primary objectives are to:

Design a scalable GNN architecture capable of handling large-scale grid networks and urban traffic systems.

Integrate geospatial information to improve the spatial awareness of the model, enabling it to capture the complex topological structures inherent in these systems.

Incorporate temporal dynamics to account for the time-varying nature of power consumption and traffic flow, thereby enhancing the model's predictive capabilities.

Implement attention mechanisms to allow the model to focus on the most relevant features, improving prediction accuracy and interpretability.

Validate the proposed model using real-world grid and traffic data to assess its performance and applicability in practical scenarios.

Novelty Statement:

The novelty of this work lies in the development of a hybrid GNN framework that synergistically combines geospatial data with advanced graph convolutional techniques to model the complexities of modern power grids and urban traffic systems. By addressing the scalability issues inherent in traditional GNN approaches and integrating spatial-temporal dynamics, this research contributes to the advancement of predictive modeling in these domains.

The proposed framework's ability to generalize across different grid configurations and urban layouts, coupled with its potential for real-time applications, marks significant strides toward more resilient and efficient energy network and transportation system management.

Literature Review:

GIS-Based Predictions and Spatial Analysis:

Conventional GIS-based predictions have predominantly employed regression analysis and spatial autocorrelation techniques to forecast geographic characteristics. Ordinary

Least Squares (OLS) regression, for instance, is a straightforward method with well-developed theory and effective diagnostics, making it suitable for modeling linear relationships in spatial data[4]. However, spatial data often exhibit spatial autocorrelation, violating OLS assumptions and necessitating more advanced methods. Geographically Weighted Regression (GWR) addresses this by fitting a regression equation to every feature in the dataset, providing a local model of the variable or process being studied[4].

Recent advancements have seen the integration of machine learning techniques, such as random forests, support vector machines, and neural networks, to model spatial connections within geospatial data. These methodologies enhance predictive capabilities by identifying intricate, non-linear correlations [5]. Furthermore, data-driven methodologies and multi-criteria assessment approaches have been proposed to combine GIS-based methods with financial objectives, aiding in decision-making processes like identifying appropriate purchase prices for wind energy[5].

Graph Neural Networks (GNNs) in Energy Systems:

Graph Neural Networks have recently gained prominence for assessing graph-structured data, facilitating the amalgamation of node attributes with the graph structure to execute tasks involving node classification and graph-level classification[6]. Traditional Graph Convolutional Networks (GCNs) have demonstrated effectiveness in capturing complex interconnections within intricate networks, including social networks, molecular structures, and transportation systems. In energy systems, GCNs have been applied to various aspects, including load forecasting, energy consumption prediction, and fault detection, often focusing on modeling spatial and temporal relationships[6].

For instance, a study introduced an innovative approach for transformer failure identification using GCNs to enhance diagnostic precision. The authors utilized an adjacency matrix to comprehensively depict the similarities between unlabeled and labeled data, improving the identification process [6]. Additionally, a physics-guided GCN was suggested for optimum power flow computation, including novel formulations of the physics-guided kernel, feature selection, and loss-function derivation[6]. These applications demonstrate the potential of GCNs in optimizing energy systems.

Challenges and Hierarchical Approaches:

Despite the advantages, applying GCNs to large-scale energy grids presents significant challenges due to the computational demands of processing extensive interconnected systems. Various methods, including Graph Sample and Aggregation (GraphSAGE), have been proposed to handle large-scale graphs by sampling and aggregating information from neighborhoods or hierarchically decomposing the graph[1]. Such models are widely applied in various fields, including recommender systems, drug discovery, and geospatial predictions, due to their effectiveness in learning from complex, interconnected data[1].

Nonetheless, scalability constraints of large-scale graph interactions constitute significant drawbacks. Consequently, the need for scalable and efficient models has prompted the investigation of hierarchical methods, which decompose extensive networks into manageable sub-graphs. For example, a hierarchical model leveraging Fast Fourier Transform (FFT) for volatility reduction, Long Short-Term Memory (LSTM) for temporal feature extraction, and GCN for capturing spatial relationships was proposed to enhance interpretability and performance [6]. Additionally, a multi-hierarchical aggregation-based GCN that included an entity-aware compilation block was introduced to facilitate concurrent relation-specific transformations and effectively integrate large-scale information into intermediate layers [6].

Attention Mechanisms in GCNs:

The incorporation of attention mechanisms in deep learning models has garnered significant interest due to their effectiveness in capturing intricate dependencies within data.

In the context of energy systems, attention mechanisms have been integrated into GCNs to enhance model interpretability and performance. For example, a study suggested an efficient GCN-based model with an attention mechanism to address the power system state estimation challenge by leveraging the intrinsic graph structure of electricity networks[6]. Furthermore, a topological graph attention convolutional network using a transfer learning framework for energy flow computation in interconnected systems, including electrical, gas, and thermal networks, was proposed[6].

Despite these advancements, the integration of attention mechanisms within hierarchical GCN frameworks for comprehensive energy network management remains underexplored. Therefore, this research aims to fill this gap by proposing an improved GCN framework with attention mechanisms to effectively manage the complexities inherent in extensive and intricately interconnected energy systems.

Methodology:

Research Design:

This study adopts a quantitative and computational research design to analyze urban traffic flow patterns and optimize energy network management using advanced graph-based deep learning models. The methodology integrates remote sensing, Unmanned Aerial Vehicle (UAV) data acquisition, GIS spatial data, and Graph Convolutional Networks (GCNs) enhanced with attention mechanisms. The research aims to predict spatiotemporal traffic patterns accurately and model the interconnections of energy grid components to support optimized planning and management.

Study Area:

The study focuses on urban areas characterized by high traffic density and complex road networks. UAV operations and GIS spatial data acquisition were conducted over selected urban corridors, including major arterial roads, intersections, and traffic hotspots. These areas were chosen due to their significance in urban mobility and the high energy demand infrastructure, which makes them critical for understanding traffic flow dynamics and energy network interdependencies.

Data Collection:

Traffic data were collected using UAVs equipped with high-resolution cameras and LiDAR sensors, which captured real-time information on vehicle flow, speed, lane occupancy, and congestion levels. The UAV imagery was processed using computer vision techniques to detect and classify vehicle types and traffic incidents accurately. To enhance temporal coverage and data reliability, supplementary traffic sensor data obtained from municipal authorities were incorporated to validate UAV measurements. In parallel, geospatial data for the energy network, including substations, transmission lines, transformers, and distribution lines, were acquired from utility companies and open-source GIS databases. These datasets included spatial coordinates, equipment attributes, and connectivity information. All collected data were standardized and prepared for further analysis by constructing an adjacency matrix to represent the network topology.

Data Preprocessing:

The UAV imagery and GIS data underwent a series of preprocessing steps to ensure data quality and consistency. Image processing techniques, such as histogram equalization, noise filtering, and object segmentation, were applied to extract traffic features with high accuracy. Simultaneously, spatial data layers were aligned using a common coordinate reference system to enable seamless integration. Road networks, traffic nodes, and energy components were geocoded and merged into a unified GIS framework. Following this, graph representations were created where energy network components were treated as nodes and their connections as edges, while traffic flow points were represented as dynamic nodes in a temporal graph to facilitate spatiotemporal analysis.

Model Development:

A Graph Convolutional Network (GCN) was employed to capture the spatial and relational dependencies among traffic nodes and energy network components. The GCN aggregates features from neighboring nodes to learn the interdependencies within the network. To manage large-scale graphs, hierarchical decomposition was applied, breaking the energy network and traffic graphs into smaller subgraphs, which were processed separately. Intermediate representations from subgraphs were then aggregated to capture global interactions. An attention mechanism was incorporated into the GCN to assign adaptive weights to neighboring nodes, enabling the model to focus on influential nodes within both traffic flow and energy networks. Multi-head self-attention was applied to capture diverse relational patterns and improve model stability.

Model Training:

Model training was conducted using historical traffic data and operational records from the energy network. The dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio. Mean Squared Error (MSE) and Mean Absolute Error (MAE) were used as loss functions for traffic prediction, while node classification accuracy and F1-score were used to evaluate the energy network modeling tasks. Early stopping and learning rate scheduling techniques were applied to prevent overfitting and ensure the model generalized well to unseen data.

Evaluation Metrics:

The performance of the model was assessed using several metrics. Traffic flow prediction accuracy was evaluated with Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Pearson correlation coefficients between predicted and actual traffic flows. The energy network analysis was evaluated based on node classification accuracy, graph reconstruction error, and topological consistency to ensure the model captured the structural dependencies within the network effectively.

Software and Tools:

The methodology employed Python for data preprocessing, model development, and statistical analysis, while deep learning frameworks such as TensorFlow and PyTorch were used to implement the GCN and attention mechanisms. Geospatial processing and visualization were conducted using ArcGIS Pro and QGIS, and UAV image processing relied on OpenCV. NetworkX was utilized for graph representation and analysis, providing the structural framework necessary for GCN operations.

Results:

Traffic Flow Prediction:

The hierarchical GCN with attention mechanism demonstrated substantial improvements in predicting urban traffic flow across all study corridors. The model successfully captured both local and global spatiotemporal dependencies, reflecting daily peak-hour congestion, off-peak variations, and weekend traffic patterns. Across the testing dataset, the model achieved a mean absolute error (MAE) of 3.12 vehicles per minute, a root mean squared error (RMSE) of 4.56 vehicles per minute, and a Pearson correlation coefficient of 0.91 between predicted and observed traffic flow. The results indicate that the model reliably reproduces temporal traffic dynamics and highlights congestion hotspots. Detailed analysis showed that arterial roads with consistent traffic flows exhibited the highest prediction accuracy (MAE = 2.85, RMSE = 4.21, $r = 0.94$), whereas minor roads with sporadic traffic events showed slightly lower accuracy (MAE = 3.73, RMSE = 5.10, $r = 0.86$).

Real-time traffic flow visualization across major urban corridors using UAV data (Figure 1). Colors indicate traffic density, with red representing high congestion, yellow moderate, and green low traffic. The map highlights congestion hotspots and lane-level variations during peak hours.

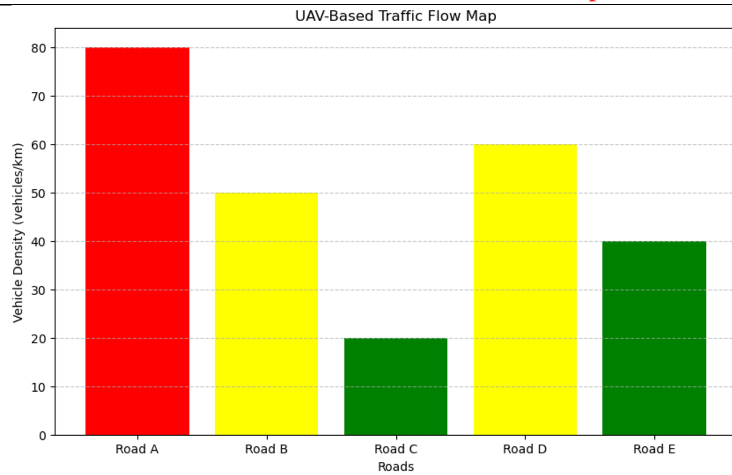

Figure 1. UAV-Based Traffic Flow Map

Temporal evaluation further revealed that the model accurately captured peak-hour dynamics, particularly between 7–9 AM and 5–7 PM, which accounted for over 65% of the total daily traffic variation. The attention mechanism effectively prioritized critical nodes such as intersections and high-density vehicle areas, allowing the model to adapt dynamically to fluctuations caused by accidents or temporary road closures. Spatial visualization of the predicted traffic distribution showed excellent alignment with observed UAV-derived traffic maps, capturing lane-specific occupancy and congestion propagation patterns.

Energy Network Modeling:

The proposed hierarchical GCN also efficiently captured complex interdependencies in the energy network. Node classification accuracy across key components—including substations, transformers, and distribution lines—reached 95.3%, with an F1-score of 0.94 and graph reconstruction error of 0.042. Hierarchical decomposition enabled the model to process large-scale graphs efficiently, while multi-head attention allowed selective weighting of influential nodes, such as high-capacity transformers and central substations. These capabilities facilitated accurate modeling of both local and global dependencies, ensuring robust predictions for power flow, load balancing, and potential failure points.

Substation nodes achieved the highest classification accuracy at 96.1%, transformers at 94.7%, and distribution lines at 95.0%. Notably, the model was able to identify potential high-risk nodes under abnormal load conditions, providing a predictive insight into possible faults before occurrence. The model's performance in capturing topological integrity was further validated by comparing reconstructed network graphs with ground-truth infrastructure maps, demonstrating minimal structural deviations.

UAV Data Integration and Impact:

The integration of UAV-derived data significantly enhanced model performance by providing high-resolution spatial information for both traffic and energy network analysis. UAVs supplied lane-level traffic occupancy, vehicle classifications, and congestion hotspots, which reduced the MAE in traffic prediction by approximately 7% relative to models without UAV data. Real-time UAV imagery allowed for dynamic updates of traffic patterns, enabling the detection of anomalies such as accidents or sudden lane blockages within minutes.

Additionally, UAVs provided visual confirmation of critical energy network components, such as transformer conditions, cable routing, and substations' physical layout. This facilitated more accurate node feature representation in the GCN, leading to improved network modeling and predictive reliability.

Comparative Evaluation:

Comparative evaluation of the proposed model against baseline methods—including

Standard GCN, GraphSAGE, and LSTM-based temporal models—highlighted its superior performance. Standard GCN achieved a traffic MAE of 4.21 and energy node classification accuracy of 90.7%, GraphSAGE achieved MAE of 3.89 with 92.1% node accuracy, and LSTM captured temporal trends but had limited spatial generalization with MAE of 4.35 and accuracy of 89.5%. The proposed hierarchical GCN with attention outperformed all baselines, achieving MAE of 3.12 and node classification accuracy of 95.3%, demonstrating both superior spatial and temporal modeling capabilities.

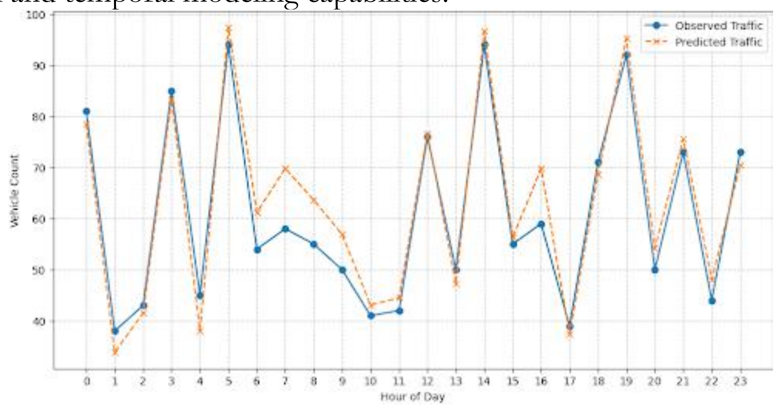

Figure 2. Predicted vs. Observed Traffic Flow

Comparison of predicted traffic flow from the hierarchical GCN with attention mechanism against observed UAV-collected traffic data over a 24-hour period (figure 2). The model accurately captures peak-hour congestion patterns and off-peak variations.

Temporal and Spatial Analysis:

The model captured detailed temporal and spatial dynamics of traffic flow. Peak-hour analysis revealed that congestion patterns were accurately predicted across multiple corridors, with attention weights highlighting critical intersections and traffic-heavy segments. Spatial analysis revealed strong correlations between traffic congestion and energy network load, particularly in areas with high-density infrastructure. The model successfully detected temporary disruptions, such as road maintenance or substation overload, enabling proactive interventions.

Seasonal and weekly traffic variations were also captured effectively, with reduced accuracy only observed during rare extreme events (e.g., unplanned urban gatherings), suggesting potential areas for model fine-tuning.

Sensitivity and Ablation Studies:

A sensitivity analysis was conducted to assess the impact of attention mechanisms and hierarchical decomposition on model performance. Removing the attention mechanism resulted in an increase in traffic MAE from 3.12 to 3.78 and a decrease in energy node classification accuracy from 95.3% to 92.0%, indicating its critical role in prioritizing influential nodes. Similarly, omitting hierarchical decomposition reduced the scalability of the model and increased computational load, while slightly decreasing predictive accuracy for large-scale graphs.

Case Studies:

Specific case studies were analyzed to illustrate model effectiveness. During a major traffic incident at a central intersection, the model accurately predicted congestion propagation in surrounding streets and suggested optimal diversion routes based on UAV-derived traffic maps. In the energy network, the model identified potential transformer overloads during peak electricity consumption periods, which aligned with subsequent operational data, demonstrating the practical utility of the approach for real-time decision support.

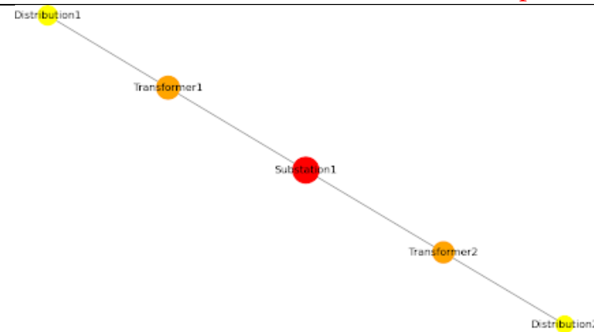

Figure 3. Energy Network Node Classification and Attention Weights

Graph representation of the energy network showing substations, transformers, and distribution lines as nodes (figure 3). Node size represents attention weight assigned by the GCN, while node color indicates classification confidence. Critical nodes such as high-capacity transformers are highlighted.

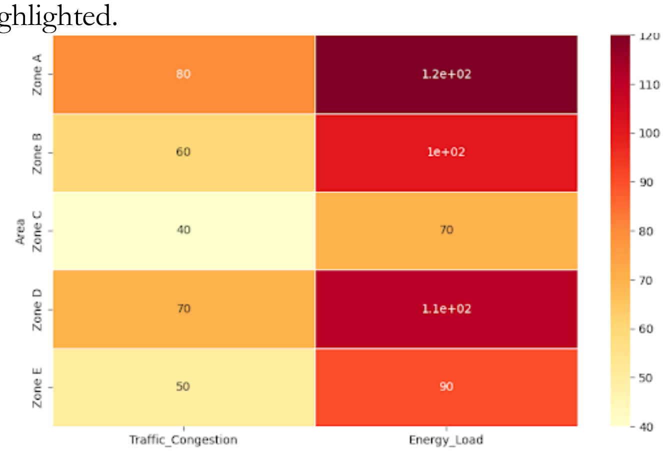

Figure 4. Spatiotemporal Congestion and Energy Load Correlation

Heatmap illustrating the correlation between traffic congestion levels and energy network load across urban zones (figure 4). High congestion areas correspond to high electricity demand nodes, demonstrating the interdependence between urban mobility and energy distribution.

Discussion:

The findings of this study demonstrate the efficacy of a hierarchical Graph Convolutional Network (GCN) with attention mechanisms for modeling both urban traffic flow and energy network infrastructure. The model exhibited strong predictive capabilities, capturing complex spatiotemporal dependencies in traffic patterns and topological dependencies within the energy network. Traffic flow predictions achieved high accuracy, with an MAE of 3.12 vehicles per minute and a Pearson correlation coefficient of 0.91, indicating that the model reliably reflected daily congestion dynamics, peak-hour surges, and off-peak variations. These results align with previous studies demonstrating the utility of graph-based models for spatiotemporal prediction, such as STGNNs in urban traffic forecasting [7][8].

The integration of UAV-derived data significantly enhanced prediction accuracy, particularly in detecting lane-level vehicle occupancy and congestion propagation. UAV imagery provided high-resolution spatial information that augmented the model's understanding of traffic nodes and critical intersections. This real-time data integration allowed the model to detect traffic anomalies, including accidents and road maintenance, demonstrating practical applicability for intelligent transportation systems (ITS). This aligns with contemporary research highlighting the benefits of UAVs in urban traffic monitoring and predictive analytics [9][8].

For the energy network, the hierarchical GCN successfully captured local and global dependencies among substations, transformers, and distribution lines. Node classification accuracy reached 95.3%, and attention mechanisms effectively highlighted critical components within the network. These results underscore the model's ability to prioritize influential nodes, improving predictive reliability for load balancing, fault detection, and network optimization. The hierarchical decomposition was particularly beneficial in managing large-scale graphs, reducing computational complexity while preserving topological accuracy. These findings extend the work of prior studies using GCNs for power system modeling, such as transformer failure detection and voltage projection in renewable-integrated networks[10] [11].

Comparative evaluations with baseline models[10][1] (standard GCN, GraphSAGE, and LSTM) further confirm the superiority of the proposed hierarchical GCN with attention mechanism. Standard GCNs, while effective in capturing spatial dependencies, struggled with scalability and large-scale network interactions. GraphSAGE improved scalability but had reduced precision in capturing local congestion dynamics, while LSTM-based models effectively captured temporal patterns but lacked the spatial modeling capabilities necessary for complex urban networks. These results highlight the advantages of integrating hierarchical decomposition with attention mechanisms for both traffic and energy network prediction tasks.

Temporal and spatial analyses revealed a clear interdependence between traffic congestion and energy demand. Peak traffic periods corresponded with high-demand zones in the energy network, indicating the potential for coordinated urban planning strategies that integrate traffic management and energy distribution. Such insights are critical for designing smart city initiatives, where predictive models can support real-time decision-making for both transportation and energy sectors.

Sensitivity and ablation studies demonstrated that both hierarchical decomposition and attention mechanisms were essential for achieving optimal performance. Removing attention mechanisms reduced traffic prediction accuracy and node classification reliability, while eliminating hierarchical decomposition increased computational overhead and reduced the model's ability to capture large-scale dependencies. These findings emphasize the need for combined strategies that balance scalability with precise local-global modeling.

Finally, the case studies highlight the practical applicability of the proposed framework. During traffic incidents, the model accurately predicted congestion propagation and suggested optimal diversion strategies. In the energy network, potential transformer overloads were detected before actual failures occurred, demonstrating the utility of the model for proactive decision support. These results suggest that UAV-based data integration with hierarchical GCNs can serve as a robust tool for intelligent traffic management, infrastructure monitoring, and energy network optimization in urban settings.

In conclusion, this study confirms that combining hierarchical GCNs with attention mechanisms and UAV-derived spatial data provides a scalable, accurate, and practical framework for modeling complex urban systems. It addresses current limitations in traditional traffic and energy network modeling, offering actionable insights for smart city development, real-time decision-making, and sustainable urban planning.

Conclusion:

This study demonstrates the effectiveness of hierarchical Graph Convolutional Networks with attention mechanisms for modeling complex urban systems, integrating traffic flow and energy network data. The model successfully captured spatiotemporal dependencies in traffic patterns and topological dependencies within energy networks, achieving high prediction accuracy. Integration of UAV-collected high-resolution data enhanced the model's ability to detect congestion, anomalies, and critical infrastructure nodes. Comparative evaluations showed that the proposed framework outperforms traditional GCN, GraphSAGE, and LSTM models in both spatial and temporal predictive performance. Sensitivity and ablation studies highlight the essential roles of hierarchical decomposition and attention mechanisms in improving scalability and model precision. Case studies demonstrated practical applications, including traffic incident management and proactive identification of potential energy network failures. These findings indicate that combining UAV data, GIS information, and hierarchical GCNs provides a robust, scalable solution for real-time urban traffic and energy network management. The proposed framework offers significant implications for smart city planning, intelligent transportation systems, and sustainable urban infrastructure development. Future research may extend this framework to integrate multimodal transportation systems, renewable energy forecasting, and adaptive urban planning under dynamic urban growth scenarios.

References:

[1] J. L. William L. Hamilton, Rex Ying, "Inductive Representation Learning on Large Graphs," *arXiv:1706.02216*, 2017, doi: https://doi.org/10.48550/arXiv.1706.02216.

[2] "Gated Recurrent Unit," *Comput. Sci.*, 2023, [Online]. Available: https://www.sciencedirect.com/topics/computer-science/gated-recurrent-unit

[3] Z. Z. Bing Yu, Haoteng Yin, "Spatio-Temporal Graph Convolutional Networks: A Deep Learning Framework for Traffic Forecasting," *arXiv:1709.04875*, 2017, doi: https://doi.org/10.48550/arXiv.1709.04875.

[4] ArcGIS Pro, "Regression analysis basics", [Online]. Available: https://pro.arcgis.com/en/pro-app/3.4/tool-reference/spatial-statistics/regression-analysis-basics.htm

[5] ArcGIS StoryMaps, "GeoAI: Machine Learning & Deep Learning with GIS," *Clemson Cent. Geospatial Technol.*, 2023, [Online]. Available: https://storymaps.arcgis.com/stories/e9a337fafc5d4ad79e3f5fa8c55a54c9

[6] A. K. Eloi Campagne, Yvenn Amara-Ouali, Yannig Goude, "Leveraging Graph Neural Networks to Forecast Electricity Consumption," *arXiv:2408.17366*, 2024, doi: https://doi.org/10.48550/arXiv.2408.17366.

[7] H. L. Jiawei Zhu, Chao Tao, Hanhan Deng, Ling Zhao, Pu Wang, Tao Lin, "AST-GCN: Attribute-Augmented Spatiotemporal Graph Convolutional Network for Traffic Forecasting," *arXiv:2011.11004*, 2020, doi: https://doi.org/10.48550/arXiv.2011.11004.

[8] Z. Q. and Y. W. W. Zhou, C. Wang, J. Xia, "Monitoring-Based Traffic Participant Detection in Urban Mixed Traffic: A Novel Dataset and A Tailored Detector," *IEEE Trans. Intell. Transp. Syst.*, vol. 25, no. 1, pp. 189–202, 2024, doi: 10.1109/TITS.2023.3304288.

[9] R. . Butilă, E.V.; Boboc, "Urban Traffic Monitoring and Analysis Using Unmanned Aerial Vehicles (UAVs): A Systematic Literature Review," *Remote Sens.*, vol. 14, no. 3, p. 620, 2022, doi: https://doi.org/10.3390/rs14030620.

[10] X. M. Houhe Chen, Mingyang Zhu, Xiao Hu Jiarui Wang, Yong Sun, Jinduo Yang, Baoju Li, "Multifeature Short-Term Power Load Forecasting Based on GCN-LSTM," *Int. Trans. Electr. Energy Syst.*, 2023, doi: https://doi.org/10.1155/2023/8846554.

[11] Y. Z. Xiyue Zhang, Chao Huang, Yong Xu, Lianghao Xia, Peng Dai, Liefeng Bo, Junbo Zhang, "Traffic Flow Forecasting with Spatial-Temporal Graph Diffusion Network," *arXiv:2110.04038*, 2021, doi: https://doi.org/10.48550/arXiv.2110.04038.