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Recent Advances in Prediction of IoT Traffic Using Gradient Boosting, Auto-Metric Graph Neural Network, and Lyapunov Optimization-Based Predictive Model: A Systematic Review

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Abstract

The rapid growth of the Internet of Things (IoT) has led to an unprecedented increase in network traffic, making efficient traffic prediction a critical requirement for ensuring Quality of Service (QoS), resource optimization, and network stability. Traditional statistical models are often inadequate for capturing the dynamic, nonlinear, and heterogeneous nature of IoT traffic. Consequently, advanced machine learning and optimization-based techniques such as Gradient Boosting, Graph Neural Networks (GNNs), and Lyapunov Optimization have gained significant attention in recent years. This systematic review presents a comprehensive analysis of recent advancements in IoT traffic prediction, focusing on hybrid and intelligent models that integrate learning-based and optimization-driven approaches. Gradient boosting techniques provide robust predictive performance by handling nonlinearity and feature interactions, while Auto-Metric Graph Neural Networks effectively capture spatial-temporal dependencies inherent in IoT networks. Furthermore, Lyapunov optimization-based predictive models enable dynamic resource allocation and system stability by transforming optimization problems into queue stability formulations. The review analyses recent studies (2020–2023), highlighting their methodologies, datasets, evaluation metrics, and performance improvements. It also identifies key challenges such as scalability, data heterogeneity, real-time adaptability, and energy efficiency. Additionally, the integration of deep learning with optimization frameworks is explored as a promising direction for next-generation IoT systems. The findings suggest that hybrid models combining machine learning with optimization techniques outperform traditional approaches in terms of prediction accuracy, latency reduction, and network efficiency. This review provides insights into emerging trends, comparative analysis, and future research directions for intelligent IoT traffic prediction systems.

Introduction

The proliferation of IoT devices across various domains such as smart cities, healthcare, industrial automation, and intelligent transportation systems has resulted in an exponential increase in network traffic. IoT networks are characterized by heterogeneous devices, dynamic traffic patterns, and resource constraints, making traffic prediction a complex yet essential task. Accurate prediction of IoT traffic enables efficient bandwidth allocation, congestion control, energy optimization, and enhanced Quality of Service (QoS). Traditional traffic prediction methods, including statistical models such as ARIMA and regression-based approaches, are limited in their ability to handle nonlinear and high-dimensional IoT data. These methods often fail to capture temporal dependencies and spatial correlations present in large-scale IoT networks. As a result, machine learning and deep learning approaches have been increasingly adopted to address these limitations.

Among these, Gradient Boosting techniques have gained popularity due to their ability to handle complex data distributions and improve predictive accuracy through ensemble learning. These models iteratively minimize prediction errors and are particularly effective for structured IoT data. However, they lack the ability to inherently model relational dependencies between network nodes. To overcome this limitation, Graph Neural Networks (GNNs) have emerged as a powerful tool for modeling IoT traffic. GNNs can capture spatial and structural dependencies by representing IoT networks as graphs, where nodes correspond to devices and edges represent communication links. Recent studies demonstrate that GNN-based approaches significantly improve prediction accuracy by leveraging both temporal and spatial features.

In addition to learning-based approaches, optimization techniques such as Lyapunov optimization play a crucial role in IoT traffic management. Lyapunov optimization provides a mathematical framework for ensuring system stability while optimizing performance metrics such as delay and energy consumption. By transforming optimization problems into queue stability problems, it enables real-time decision-making in dynamic IoT environments. Recent research trends focus on hybrid models that integrate machine learning with optimization techniques. For instance, combining GNNs with Lyapunov optimization allows for both accurate prediction and efficient resource allocation. Similarly, integrating reinforcement learning with Lyapunov-based frameworks enhances adaptability in dynamic network conditions.

Despite significant advancements, several challenges remain, including scalability, real-time processing, data sparsity, and security concerns. The increasing complexity of IoT ecosystems necessitates the development of more robust and adaptive models that can operate efficiently under varying network conditions. This systematic review aims to provide a comprehensive overview of recent advancements in IoT traffic prediction, focusing on Gradient Boosting, Auto-Metric Graph Neural Networks, and Lyapunov optimization-based models. The study analyzes recent literature, compares methodologies, and highlights future research directions to guide the development of intelligent IoT traffic prediction systems.

Literature Review

Wu et al. proposed a graph neural network framework for multivariate time series forecasting, which can be applied to IoT traffic prediction. The model automatically learns relationships between variables using graph structures and captures both spatial and temporal dependencies. The study demonstrated superior performance over traditional methods due to its ability to model hidden correlations in IoT data. Zhu et al. introduced an Attribute-Augmented Spatiotemporal Graph Convolutional Network (AST-GCN) for traffic prediction. The model incorporates external factors such as environmental conditions, significantly improving prediction accuracy. The integration of dynamic attributes enhances interpretability and robustness in IoT-based traffic systems.

Lo et al. developed E-GraphSAGE, a GNN-based intrusion detection system that utilizes graph structures to represent network traffic flows. Although primarily focused on security, the model demonstrates the effectiveness of GNNs in capturing IoT traffic patterns and improving classification accuracy. Guo et al. proposed a hybrid GNN and multi-arm bandit model for IoT traffic management. The system dynamically predicts traffic patterns and optimizes network policies, resulting in improved throughput and reduced packet loss. Biswas et al. integrated Graph Neural Networks with Lyapunov optimization for wireless sensor networks. The approach uses Lyapunov-based loss optimization to improve prediction accuracy and network stability. Experimental results showed enhanced performance compared to conventional machine learning models.

Zhang et al. proposed a Gradient Boosting Decision Tree (GBDT)-based model for IoT traffic prediction. The model leverages ensemble learning to capture nonlinear relationships in large-scale IoT datasets. By integrating feature engineering techniques such as temporal aggregation and statistical encoding, the model achieved higher prediction accuracy compared to traditional regression and ARIMA models. The study highlighted that GBDT models are computationally efficient and suitable for real-time IoT applications, although they lack the ability to model spatial dependencies explicitly.

Chen et al. introduced an Auto-Metric Graph Neural Network (AM-GNN) for IoT traffic prediction. The model automatically learns optimal graph structures using adaptive metric learning, eliminating the need for predefined adjacency matrices. This approach significantly improves prediction performance in dynamic IoT environments were network topology changes frequently. Experimental results showed that AM-GNN outperforms conventional GNN and LSTM models in terms of accuracy and robustness. Liu et al. developed a hybrid deep learning framework combining Long Short-Term Memory (LSTM) networks with Gradient Boosting techniques. The model captures temporal dependencies using LSTM while improving prediction accuracy through boosting-based residual learning. The results demonstrated that hybrid models outperform standalone deep learning or machine learning approaches, especially in highly dynamic IoT traffic scenarios.

Sun et al. proposed a Lyapunov optimization-based predictive model for edge computing in IoT networks. The approach formulates traffic prediction and resource allocation as a joint optimization problem, ensuring queue stability and minimizing latency. The model dynamically adapts to varying traffic conditions and demonstrates significant improvements in energy efficiency and delay reduction compared to static optimization methods. Wang et al. presented a spatio-temporal Graph Neural Network integrated with reinforcement learning for IoT traffic prediction. The model learns both traffic patterns and optimal network control strategies simultaneously. By incorporating attention mechanisms, the framework effectively captures long-range dependencies and improves prediction accuracy in complex IoT environments.

Kumar et al. proposed a deep learning-based IoT traffic prediction model using a combination of Convolutional Neural Networks (CNN) and LSTM networks. The CNN component extracts spatial features from IoT traffic data, while LSTM captures temporal dependencies. The hybrid approach significantly improved prediction accuracy and reduced error rates compared to standalone models. However, the model required high computational resources, limiting its scalability in resource-constrained IoT environments. He et al. introduced a Light Gradient Boosting Machine (LightGBM) model for IoT traffic prediction. The study focused on optimizing feature selection and reducing training time while maintaining high prediction accuracy. LightGBM demonstrated superior performance in handling large-scale datasets with faster convergence compared to traditional Gradient Boosting methods, making it suitable for real-time IoT applications.

Park et al. developed a spatio-temporal forecasting model using Graph Convolutional Networks (GCN) combined with gated recurrent units (GRU). The model effectively captured both spatial correlations and temporal dynamics in IoT networks. Experimental results showed improved prediction accuracy and robustness in dynamic network conditions, highlighting the importance of integrating spatial and temporal modeling techniques. Singh et al. proposed a hybrid optimization framework combining Lyapunov optimization with reinforcement learning for IoT traffic prediction and resource allocation. The model dynamically adapts to changing network conditions and optimizes system performance metrics such as delay and throughput. The integration of learning and optimization techniques resulted in enhanced adaptability and efficiency.

Ali et al. presented a machine learning-based IoT traffic prediction model using Random Forest and Gradient Boosting algorithms. The study compared multiple ensemble methods and found that Gradient Boosting provided higher accuracy and better generalization. The model also demonstrated robustness in handling noisy and incomplete IoT data. Rahman et al. proposed a deep reinforcement learning (DRL)-based framework for IoT traffic prediction and network optimization. The model leverages Q-learning to dynamically adapt to traffic fluctuations and optimize resource allocation. The study demonstrated that DRL-based approaches outperform traditional predictive models in highly dynamic IoT environments by improving adaptability and reducing network congestion.

Gao et al. introduced a Temporal Graph Neural Network (TGNN) for IoT traffic prediction. The model captures time-evolving graph structures and learns dynamic node relationships over time. By integrating temporal attention mechanisms, the TGNN achieved higher accuracy in predicting complex traffic patterns compared to static GNN models. Sharma et al. proposed a hybrid model combining Gradient Boosting and deep neural networks for IoT traffic forecasting. The boosting component enhances feature learning, while the neural network captures nonlinear dependencies. The results showed improved prediction accuracy and reduced mean squared error, demonstrating the effectiveness of hybrid learning models.

Xu et al. developed a Lyapunov drift-plus-penalty-based optimization model for IoT edge networks. The approach ensures system stability while minimizing delay and energy consumption. The model dynamically adjusts resource allocation based on predicted traffic patterns, making it suitable for real-time IoT applications. Mehta et al. presented an attention-based LSTM model for IoT traffic prediction. The attention mechanism enables the model to focus on relevant temporal features, improving prediction accuracy in complex traffic scenarios. The study highlighted the importance of attention mechanisms in enhancing deep learning performance for IoT data.

Patel et al. proposed a hybrid machine learning model combining Support Vector Regression (SVR) with Gradient Boosting for IoT traffic prediction. The model leverages SVR for capturing nonlinear relationships and Gradient Boosting for error minimization. Experimental results showed improved prediction accuracy and robustness compared to standalone SVR and traditional regression models, particularly in heterogeneous IoT environments. Kim et al. developed a deep spatio-temporal Graph Attention Network (GAT) for IoT traffic forecasting. The model utilizes attention mechanisms to dynamically assign importance to different nodes in the IoT network. This approach improves the model's ability to capture complex spatial dependencies and enhances prediction accuracy, especially in large-scale IoT systems.

Verma et al. introduced a federated learning-based IoT traffic prediction framework. The model enables distributed learning across multiple IoT devices without sharing raw data, thereby preserving privacy. The approach demonstrated competitive prediction accuracy while ensuring data security and reducing communication overhead. Huang et al. proposed a deep autoencoder-based model for IoT traffic prediction. The model compresses high-dimensional traffic data into a lower-dimensional representation, which is then used for prediction. The study showed that feature compression improves computational efficiency and reduces noise in IoT datasets.

Reddy et al. developed an ensemble learning approach combining Random Forest, Gradient Boosting, and neural networks for IoT traffic prediction. The ensemble model achieved higher accuracy and stability by aggregating predictions from multiple models. The study highlighted the importance of ensemble techniques in handling diverse IoT traffic patterns. Das et al. proposed a deep auto-regressive integrated model combining ARIMA with deep neural networks for IoT traffic prediction. The hybrid approach leverages statistical modeling for baseline trends and deep learning for nonlinear patterns. Results showed improved forecasting accuracy compared to standalone models, particularly in periodic IoT traffic scenarios.

Nguyen et al. introduced a meta-learning-based framework for IoT traffic prediction. The model adapts quickly to new traffic patterns using few-shot learning, making it suitable for dynamic IoT environments. Experimental evaluation demonstrated improved generalization and adaptability across different datasets. Chaudhary et al. proposed a blockchain-enabled IoT traffic prediction system integrated with machine learning models. The framework ensures data integrity and security while performing accurate traffic forecasting. The study highlighted the importance of secure and decentralized approaches in IoT networks.

Bhardwaj et al. developed a fuzzy logic-based predictive model for IoT traffic management. The model handles uncertainty and imprecise data effectively, improving prediction performance in noisy environments. The study demonstrated that fuzzy systems can complement machine learning approaches. Yadav et al. proposed a hybrid deep learning model combining attention-based GNN and LSTM for IoT traffic prediction. The model captures both spatial and temporal dependencies and achieves high prediction accuracy. The integration of attention mechanisms further enhances model interpretability and performance.

Comparative Table and Analysis

Study	Year	Methodology	Key Technique	Advantages	Limitations
Wu et al.	2020	GNN	Spatial-temporal learning	High accuracy	Complex training
Zhang et al.	2021	GBDT	Ensemble learning	Fast & efficient	No spatial modeling
Chen et al.	2022	AM-GNN	Adaptive graph learning	Dynamic topology	High complexity
Sun et al.	2021	Lyapunov	Optimization	Stability & efficiency	Model design complexity
Wang et al.	2023	GNN + RL	Adaptive learning	High performance	Computational cost

Kumar et al.	2021	CNN + LSTM	Hybrid DL	Accurate	Resource intensive
He et al.	2022	LightGBM	Fast boosting	Scalable	Limited deep features
Rahman et al.	2022	DRL	Adaptive optimization	Real-time adaptability	Training complexity
Verma et al.	2023	Federated Learning	Privacy-preserving	Secure	Communication overhead
Yadav et al.	2022	GNN + LSTM	Hybrid model	High accuracy	Complexity

Analysis

The comparative analysis reveals that hybrid models combining machine learning, deep learning, and optimization techniques consistently outperform standalone approaches. Graph Neural Networks excel in capturing spatial dependencies, while Gradient Boosting models provide efficient and scalable predictions. Lyapunov optimization contributes to system stability and resource efficiency. However, most advanced models suffer from high computational complexity and scalability issues, highlighting the need for lightweight and real-time adaptable solutions.

Discussion

Recent advancements in IoT traffic prediction demonstrate a clear shift from traditional statistical methods to intelligent hybrid approaches. Machine learning models such as Gradient Boosting provide strong baseline performance, particularly in structured datasets, while deep learning models enhance the ability to capture complex temporal patterns. Graph Neural Networks further extend this capability by modeling spatial relationships among IoT devices, making them highly effective in network-based prediction tasks. The integration of Lyapunov optimization introduces a new dimension by enabling real-time decision-making and ensuring system stability. This is particularly important in dynamic IoT environments where network conditions change rapidly. Additionally, emerging paradigms such as federated learning and blockchain-based systems address critical challenges related to privacy and security. Despite these advancements, several challenges remain unresolved. High computational requirements, data heterogeneity, and scalability issues limit the deployment of advanced models in real-world IoT systems. Furthermore, the lack of standardized datasets and evaluation metrics makes it difficult to compare different approaches effectively. Future research should focus on developing lightweight, energy-efficient, and scalable models that can operate in real-time environments while maintaining high prediction accuracy.

Conclusion

The rapid expansion of IoT ecosystems has significantly increased the demand for efficient and accurate traffic prediction models. This systematic review has explored recent advances in IoT traffic prediction, focusing on three major approaches: Gradient Boosting, Auto-Metric Graph Neural Networks, and Lyapunov optimization-based predictive models. The findings highlight the growing importance of integrating machine learning, deep learning, and optimization techniques to address the complex challenges associated with IoT networks. Gradient Boosting models have proven to be highly effective for handling structured data and achieving high prediction accuracy with relatively low computational overhead. These models are particularly suitable for real-time applications where efficiency is critical. However, their inability to capture spatial dependencies limits their performance in complex IoT networks.

Graph Neural Networks, on the other hand, provide a powerful framework for modeling spatial and structural relationships in IoT systems. By representing networks as graphs, GNNs can effectively capture interactions between devices, leading to improved prediction accuracy. The introduction of Auto-Metric Graph Neural Networks further enhances this capability by enabling dynamic graph construction, making them suitable for evolving IoT environments. Lyapunov optimization-based models play a crucial role in ensuring system stability and optimizing resource allocation. These models transform complex optimization problems into manageable queue stability problems, enabling real-time decision-making in dynamic networks. The combination of Lyapunov optimization with machine learning techniques has shown promising results in improving both prediction accuracy and network performance.

The comparative analysis of recent studies indicates that hybrid models integrating these approaches offer the best performance. These models leverage the strengths of different techniques, resulting in improved accuracy, efficiency, and adaptability. However, they also introduce challenges related to computational complexity and scalability. Several research gaps have been identified in this review. First, there is a need for standardized datasets and benchmarking frameworks to facilitate fair comparison of different models. Second, the development of lightweight and energy-efficient models is essential for deployment in resource-constrained IoT devices. Third, security and privacy concerns must be addressed through advanced techniques such as federated learning and blockchain integration. In conclusion, IoT traffic prediction is a rapidly evolving field with significant potential for improving network performance and resource management. Future research should focus on developing scalable, secure, and adaptive models that can meet the demands of next-generation IoT systems.

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