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A Survey of Methods and Architectures for Prediction of IoT Traffic Using Gradient Boosting, Auto-Metric Graph Neural Network, and Lyapunov Optimization-Based Predictive Model

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Abstract

The exponential growth of the Internet of Things (IoT) has resulted in massive volumes of heterogeneous and dynamic traffic, necessitating accurate prediction models for efficient network management. Traditional statistical approaches are insufficient to capture the nonlinear, temporal, and spatial dependencies inherent in IoT traffic. Consequently, advanced machine learning, deep learning, and optimization-based models have been widely adopted. This survey explores recent methods and architectures for IoT traffic prediction, focusing on Gradient Boosting, Auto-Metric Graph Neural Networks (AM-GNN), and Lyapunov optimization-based predictive models. Gradient Boosting techniques provide high accuracy and scalability through ensemble learning, while Graph Neural Networks effectively model spatial relationships by representing IoT devices as graph structures. GNN-based models are particularly effective in capturing hidden dependencies in multivariate time series data. Furthermore, Lyapunov optimization provides a robust framework for ensuring system stability and dynamic resource allocation by transforming optimization problems into queue stability problems. Recent hybrid approaches combining GNNs with optimization techniques have demonstrated significant improvements in prediction accuracy, latency reduction, and energy efficiency. This survey systematically reviews recent literature (2020–2023), analyses key methodologies, and highlights emerging trends such as federated learning, reinforcement learning, and hybrid AI models. It also identifies major challenges including scalability, computational complexity, and data heterogeneity. The study concludes with future research directions aimed at developing efficient, scalable, and intelligent IoT traffic prediction systems.

Introduction

The Internet of Things (IoT) has transformed modern communication systems by enabling seamless connectivity among billions of devices across domains such as smart cities, healthcare, transportation, and industrial automation. This rapid expansion has led to a dramatic increase in network traffic, creating challenges in terms of congestion, latency, energy consumption, and resource allocation. Accurate prediction of IoT traffic has therefore become essential for ensuring efficient network operation and

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maintaining Quality of Service (QoS). Traditional traffic prediction models such as autoregressive integrated moving average (ARIMA) and linear regression have been widely used in early research. However, these methods fail to capture the nonlinear and complex patterns of IoT traffic. IoT data is inherently high-dimensional, time-dependent, and spatially correlated, making it difficult for conventional models to provide accurate predictions.

To address these challenges, machine learning and deep learning approaches have gained significant attention. Gradient Boosting models, including LightGBM and XGBoost, have shown strong performance in handling structured IoT data due to their ability to model nonlinear relationships and minimize prediction errors iteratively. These models are highly efficient and scalable, making them suitable for real-time applications. In parallel, Graph Neural Networks (GNNs) have emerged as a powerful tool for modeling IoT networks. Since IoT systems can naturally be represented as graphs where devices are nodes and communication links are edges, GNNs can effectively capture spatial dependencies and interactions. Recent studies show that GNN-based models significantly outperform traditional methods by learning hidden relationships among variables and capturing spatio-temporal dynamics. Moreover, spatio-temporal GNN architectures have become a dominant approach in traffic forecasting due to their ability to jointly model spatial and temporal features.

Another important advancement is the use of Lyapunov optimization in IoT traffic management. Lyapunov optimization provides a mathematical framework for controlling dynamic systems by minimizing queue backlogs while optimizing performance metrics such as delay and energy consumption. It has been widely applied in edge computing and IoT networks for resource allocation and system stability. Recent work integrates Lyapunov optimization with machine learning models to enable real-time adaptive decision-making and predictive control The integration of these approaches has led to the development of hybrid models that combine learning-based prediction with optimization-based control. For example, combining GNNs with optimization techniques allows for accurate prediction while ensuring efficient resource utilization. Similarly, reinforcement learning and federated learning have been introduced to improve adaptability and privacy in distributed IoT environments.

Despite these advancements, several challenges remain. These include scalability issues due to the large number of IoT devices, computational complexity of deep learning models, lack of standardized datasets, and security concerns. Addressing these challenges is crucial for the deployment of intelligent IoT traffic prediction systems in real-world scenarios. This survey aims to provide a comprehensive overview of recent methods and architectures for IoT traffic prediction, focusing on Gradient Boosting, Auto-Metric GNNs, and Lyapunov optimization-based models. It systematically reviews existing literature, compares methodologies, and identifies future research directions.

Literature Review

Wu et al. proposed a GNN-based framework for multivariate time series forecasting that automatically learns relationships between variables. The model captures both spatial and temporal dependencies, achieving superior performance over traditional methods. Zhu et al. developed AST-GCN, which integrates external attributes such as environmental factors into spatio-temporal graph models. The approach improves prediction accuracy and interpretability in traffic forecasting scenarios.

Lo et al. introduced E-GraphSAGE, a GNN-based model for IoT network traffic analysis. The model effectively captures topological and edge features, demonstrating improved performance in network prediction tasks. Biswas et al. integrated GNN with Lyapunov optimization for IoT systems. The model ensures both accurate prediction and system stability, highlighting the effectiveness of combining learning and optimization techniques. Recent work on fog computing integrates Lyapunov optimization with LSTM models for predictive task allocation, improving energy efficiency and reducing latency in IoT systems.

Zhang et al. explored the use of Gradient Boosting Decision Trees (GBDT) for IoT traffic prediction. The model leverages ensemble learning to iteratively reduce prediction errors and handle nonlinear data distributions effectively. The study demonstrated that GBDT outperforms traditional statistical models such as ARIMA in terms of prediction accuracy and computational efficiency. However, it lacks the ability to explicitly model spatial relationships among IoT devices.

Chen et al. proposed an Auto-Metric Graph Neural Network (AM-GNN) that automatically learns the graph structure using metric learning techniques. This eliminates the dependency on predefined adjacency matrices, making the model highly adaptable to dynamic IoT environments. The approach showed improved robustness and accuracy compared to conventional GNN models. Liu et al. introduced a hybrid framework combining LSTM networks with Gradient Boosting. The LSTM component captures temporal dependencies, while Gradient Boosting enhances prediction accuracy by correcting residual errors. The hybrid model significantly improved forecasting performance in highly dynamic IoT traffic scenarios.

Sun et al. developed a Lyapunov optimization-based model for IoT edge networks. The framework jointly optimizes traffic prediction and resource allocation by minimizing queue backlog and system delay. The results showed improved energy efficiency and reduced latency compared to static optimization methods. Wang et al. proposed a spatio-temporal Graph Neural Network integrated with reinforcement learning. The model simultaneously predicts IoT traffic and optimizes network control policies. The incorporation of attention mechanisms further enhances its ability to capture long-range dependencies, leading to improved prediction accuracy in complex IoT environments.

Kumar et al. proposed a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for IoT traffic prediction. The CNN component extracts spatial features, while LSTM captures temporal dependencies. The model achieved significant improvements in prediction accuracy; however, it required high computational resources, limiting its deployment in edge-based IoT systems.

He et al. introduced Light Gradient Boosting Machine (LightGBM) for efficient IoT traffic forecasting. The model emphasizes fast training speed and scalability while maintaining high prediction accuracy. Feature selection and data preprocessing techniques further enhanced model performance, making it suitable for large-scale IoT datasets. Park et al. developed a spatio-temporal forecasting model using Graph Convolutional Networks (GCN) combined with Gated Recurrent Units (GRU). The model effectively captures both spatial dependencies and temporal dynamics in IoT traffic. Experimental results showed improved robustness and prediction accuracy compared to standalone models.

Singh et al. proposed a hybrid framework integrating Lyapunov optimization with reinforcement learning for IoT traffic prediction and resource allocation. The model dynamically adapts to varying network conditions and optimizes performance metrics such as latency, throughput, and energy efficiency. Ali et al. conducted a comparative study using Random Forest and Gradient Boosting for IoT traffic prediction. The results indicated that Gradient Boosting outperformed other ensemble methods in terms of accuracy and robustness, particularly when dealing with noisy and incomplete IoT datasets.

Rahman et al. proposed a deep reinforcement learning (DRL)-based framework for IoT traffic prediction and adaptive resource management. The model utilizes Q-learning to dynamically adjust to changing traffic patterns and optimize network performance. The results demonstrated improved adaptability and reduced congestion compared to traditional prediction models, especially in highly dynamic IoT environments.

Gao et al. introduced a Temporal Graph Neural Network (TGNN) model for IoT traffic prediction. The framework captures time-evolving relationships between nodes and integrates temporal attention mechanisms to enhance prediction accuracy. The model significantly outperformed static GNN models by effectively learning dynamic traffic patterns.

Sharma et al. proposed a hybrid architecture combining Gradient Boosting with deep neural networks. The boosting component improves feature learning and reduces prediction error, while the neural network captures nonlinear relationships in IoT traffic data. The hybrid model achieved lower mean squared error and higher prediction accuracy compared to standalone approaches. Xu et al. developed a Lyapunov drift-plus-penalty optimization model for IoT edge networks. The approach ensures system stability while minimizing delay and energy consumption. By dynamically adjusting resource allocation based on predicted traffic, the model supports real-time IoT applications effectively.

Mehta et al. introduced an attention-based LSTM model for IoT traffic prediction. The attention mechanism allows the model to focus on important temporal features, improving prediction performance in complex and noisy IoT datasets. The study highlighted the role of attention mechanisms in enhancing deep learning models. Patel et al. proposed a hybrid regression framework combining Support Vector Regression (SVR) with Gradient Boosting for IoT traffic prediction. The SVR component captures nonlinear relationships, while Gradient Boosting refines prediction accuracy by minimizing residual errors. The model demonstrated improved robustness and accuracy in heterogeneous IoT environments.

Kim et al. introduced a Graph Attention Network (GAT)-based model for IoT traffic prediction. By assigning adaptive attention weights to nodes, the model effectively captures complex spatial dependencies. The study showed that GAT-based approaches outperform traditional GNN models in large-scale IoT networks. Verma et al.

proposed a federated learning-based IoT traffic prediction system. The framework enables distributed model training across multiple IoT devices without sharing raw data, thereby ensuring privacy and security. The results showed competitive prediction accuracy with reduced communication overhead.

Huang et al. developed a deep autoencoder-based approach for IoT traffic prediction. The model reduces dimensionality and noise in high-dimensional IoT datasets, improving computational efficiency and prediction performance. Reddy et al. proposed an ensemble learning model combining Random Forest, Gradient Boosting, and neural networks. The ensemble approach improved prediction accuracy and stability by aggregating multiple model outputs, making it suitable for diverse IoT traffic scenarios.

Das et al. proposed a hybrid ARIMA–Deep Learning model for IoT traffic prediction. The statistical ARIMA component captures linear trends, while deep neural networks model nonlinear patterns. The hybrid approach demonstrated improved prediction accuracy, particularly in periodic IoT traffic scenarios. Nguyen et al. introduced a meta-learning-based IoT traffic prediction model capable of adapting quickly to new environments using few-shot learning. The model enhances generalization and performs well across diverse IoT datasets, making it suitable for dynamic network conditions.

Chaudhary et al. developed a blockchain-integrated IoT traffic prediction system. The framework ensures data security and integrity while applying machine learning techniques for accurate prediction. The approach addresses security challenges in distributed IoT environments. Bhardwaj et al. proposed a fuzzy logic-based predictive model for IoT traffic management. The model effectively handles uncertainty and imprecise data, improving prediction reliability in noisy environments. Yadav et al. presented a hybrid attention-based GNN-LSTM model for IoT traffic prediction. The model captures both spatial and temporal dependencies while improving interpretability through attention mechanisms. The results showed superior performance compared to traditional deep learning models.

Comparative Table and Analysis

Study	Year	Technique	Model Type	Key Strength	Limitation
Wu et al.	2020	GNN	Deep Learning	Captures spatial relations	Complex training
Zhang et al.	2021	GBDT	ML	Fast & scalable	No spatial modeling
Chen et al.	2022	AM-GNN	Deep Learning	Adaptive graph learning	High complexity
Sun et al.	2021	Lyapunov	Optimization	Stability & efficiency	Design complexity
Wang et al.	2023	GNN+RL	Hybrid	Adaptive & accurate	High computation
Kumar et al.	2021	CNN+LSTM	Hybrid DL	High accuracy	Resource intensive
He et al.	2022	LightGBM	ML	Fast training	Limited deep features
Rahman et al.	2022	DRL	Hybrid	Dynamic adaptation	Training complexity
Kim et al.	2022	GAT	DL	Strong spatial modeling	Scalability issues
Verma et al.	2023	Federated	ML	Privacy-preserving	Communication overhead
Reddy et al.	2022	Ensemble	ML/DL	Robust & stable	Complex integration
Yadav et al.	2022	GNN+LSTM	Hybrid	High accuracy	Computational cost

Analysis

The comparative analysis highlights that no single model is sufficient to address all challenges in IoT traffic prediction. Gradient Boosting models are efficient and scalable but lack spatial awareness. Graph Neural Networks excel in capturing spatial dependencies but require high computational resources. Lyapunov optimization provides system stability and efficient resource allocation but does not inherently perform prediction. Hybrid models integrating GNNs, boosting techniques, and optimization frameworks demonstrate superior performance by leveraging the strengths of each approach. However, they introduce complexity and scalability challenges. Emerging approaches such as federated learning and meta-learning address privacy and adaptability but require further research for practical deployment.

Discussion

The evolution of IoT traffic prediction models reflects a transition from traditional statistical approaches to advanced hybrid intelligent systems. Machine learning models such as Gradient Boosting provide strong baseline performance and are particularly effective for structured data. However, they lack the ability to model spatial dependencies inherent in IoT networks. Graph Neural Networks address this limitation by representing IoT systems as graph structures, enabling the modeling of complex relationships between devices. The integration of attention mechanisms further enhances their ability to capture long-range dependencies. Meanwhile, Lyapunov optimization introduces a control-theoretic perspective, ensuring system stability and efficient resource utilization.

Recent research trends emphasize hybrid models that combine prediction and optimization, offering improved performance in dynamic environments. Additionally, federated learning and blockchain technologies are gaining attention for addressing privacy and security concerns. Despite these advancements, challenges such as computational complexity, scalability, and lack of standardized datasets remain significant barriers. Future research should focus on developing lightweight, scalable, and energy-efficient models capable of real-time deployment in IoT systems.

Conclusion

The rapid expansion of IoT networks has created an urgent need for efficient and accurate traffic prediction models to ensure optimal network performance and resource utilization. This survey has provided a comprehensive analysis of recent methods and architectures for IoT traffic prediction, focusing on Gradient Boosting, Auto-Metric Graph Neural Networks, and Lyapunov optimization-based predictive models. Gradient Boosting techniques have demonstrated strong performance in handling structured IoT data and achieving high prediction accuracy with relatively low computational cost. These models are particularly suitable for real-time applications; however, their inability to capture spatial relationships limits their effectiveness in complex IoT environments.

Graph Neural Networks have emerged as a powerful solution for modeling IoT systems due to their ability to represent network structures and capture spatial dependencies. The development of Auto-Metric GNNs further enhances this capability by enabling dynamic graph construction, making them suitable for evolving IoT networks. Despite their advantages, GNN-based models require significant computational resources, posing challenges for deployment in resource-constrained environments. Lyapunov optimization-based models provide a robust framework for ensuring system stability and optimizing resource allocation. By transforming optimization problems into queue stability problems, these models enable real-time decision-making in dynamic IoT environments. The integration of Lyapunov optimization with machine learning techniques has shown promising results in improving both prediction accuracy and system performance.

The comparative analysis of recent studies indicates that hybrid models integrating machine learning, deep learning, and optimization techniques offer the best performance. These models combine the strengths of different approaches, resulting in improved accuracy, adaptability, and efficiency. However, they also introduce challenges related to computational complexity and scalability. Several research gaps have been identified in this survey. First, there is a need for standardized datasets and evaluation metrics to facilitate fair comparison of different models. Second, the development of lightweight and energy-efficient models is essential for deployment in real-world IoT systems. 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 to improve network performance and enable intelligent decision-making. 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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