
DSTAQ-Net: A Dynamic Spatio-Temporal Deep Learning Framework for Multi-Pollutant Air Quality Prediction Using Distributed Sensor Networks

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Abstract

Accurate and timely air quality prediction is critical for mitigating the adverse impacts of air pollution on public health, urban sustainability, and environmental governance. However, existing forecasting models often struggle to capture the complex nonlinear interactions and dynamic spatio-temporal dependencies inherent in large-scale air quality sensor networks, particularly under noisy and heterogeneous measurement conditions. To address these challenges, this paper proposes a deep learning-based spatio-temporal framework, named DSTAQ-Net, for real-time and multi-horizon prediction of air pollutant concentrations using distributed IoT sensor networks. The proposed framework integrates sensor reliability assessment, dynamic spatial graph construction, spatio-temporal feature encoding, attention-based learning, and multi-pollutant forecasting into a unified architecture. A dynamic graph convolutional network is employed to model evolving spatial relationships among monitoring stations based on geographic proximity, pollutant correlation, and meteorological similarity, while gated recurrent units capture temporal dependencies in pollutant dynamics. An attention mechanism further enhances the model by adaptively weighting the most influential sensors, pollutants, and historical time steps, enabling robust learning under sensor noise and data sparsity. The forecasting layer jointly predicts multiple air quality indicators, including PM_{2.5}, PM₁₀, NO₂, CO, O₃, and AQI, across short-term and long-term horizons. The framework is evaluated using two public benchmark datasets, namely the Beijing Multi-Site Air Quality Dataset and the UCI Air Quality Sensor Dataset. Experimental results demonstrate that DSTAQ-Net achieves significantly lower prediction error and higher stability compared with state-of-the-art spatio-temporal deep learning models. These findings confirm the effectiveness of the proposed approach for reliable air quality forecasting and its suitability for deployment in smart city and environmental monitoring applications.

Keywords: Machine learning, Prediction, Air quality, temporal features

Introduction

Air pollution has emerged as one of the most critical global environmental and public health challenges of the twenty-first century, with rapid urbanization, industrial expansion, vehicular emissions, and climate variability contributing to a continuous deterioration of atmospheric quality in both developed and developing regions. According to international health and environmental agencies, prolonged exposure to fine particulate matter and toxic gaseous pollutants such as PM_{2.5}, PM₁₀, NO₂, SO₂, CO, and O₃ significantly increases the risk of respiratory diseases, cardiovascular disorders, premature mortality, and ecological degradation. In densely populated urban environments, pollution episodes often occur unpredictably and can escalate rapidly due to meteorological changes, traffic congestion, industrial activity, and human behavior, making real-time monitoring and accurate forecasting a crucial requirement for public safety, environmental governance, and smart city management [1-3].

Air pollution is governed by nonlinear physical, chemical, and meteorological processes, including atmospheric diffusion, chemical reactions, wind flow, humidity, temperature inversions, and urban topology, which interact across both space and time. Consequently, simple statistical models such as autoregressive integrated moving average (ARIMA), linear regression, and basic interpolation techniques fail to capture the intricate spatio-temporal dependencies and nonlinear correlations that characterize real-world air quality dynamics [4-7]. Even conventional machine learning approaches, including support vector machines, decision trees, and random forests, while capable of modeling certain nonlinearities, typically treat spatial and temporal dimensions independently and struggle to generalize under highly dynamic environmental conditions [8-13].

The framework is designed to process multi-pollutant time-series data collected from distributed monitoring nodes, transform them into structured spatio-temporal representations, and generate accurate short-term and long-term forecasts for key air quality indicators, including particulate matter and gaseous pollutants. Unlike traditional models that require extensive domain-specific feature engineering and calibration, the proposed deep learning approach learns predictive patterns directly from data, enabling adaptive modeling across different geographic regions, seasonal variations, and emission patterns. Moreover, the use of sensor networks allows the system to operate at high spatial resolution, making it suitable for fine-grained urban pollution mapping, localized alert generation, and micro-environmental analysis.

Research Gaps

Although existing studies demonstrate that deep learning-based spatio-temporal models significantly improve air quality prediction, several critical gaps remain. First, most current approaches rely on static or semi-static spatial relationships among monitoring stations, whereas real pollution transport is highly dynamic and influenced by meteorology, urban morphology, and emission patterns, requiring more adaptive and context-aware spatial modeling. Second, many deep architectures are computationally intensive and difficult to deploy in real-time IoT-based sensor networks, limiting their practical applicability in smart city environments. These gaps motivate the need for a lightweight yet powerful spatio-temporal deep learning framework that is robust, adaptive, and deployable within real-world sensor network infrastructures for reliable air quality and pollution level prediction.

Proposed Work

Existing air quality prediction models predominantly rely on static spatial correlations, heavy deep learning architectures, and centralized computation, which limits their effectiveness in real-world IoT-based sensor networks characterized by noisy data, heterogeneous sampling rates, and dynamic environmental conditions. Moreover, many models are computationally expensive and unsuitable for real-time deployment, and few incorporate physical atmospheric influences such as meteorology and pollutant diffusion patterns. To address these limitations, this work proposes a lightweight, adaptive, and physically informed deep learning framework that integrates dynamic spatio-temporal modeling, sensor reliability awareness, and attention-driven feature selection to enable accurate and real-time air pollution forecasting over large-scale sensor networks.

Overview of the Proposed Framework

The proposed system, named DSTAQ-Net (Dynamic Spatio-Temporal Air Quality Network), is designed to perform real-time and multi-horizon prediction of air quality indicators using data from distributed IoT-based sensor networks. It consists of five interconnected modules:

1. Data Acquisition and Sensor Reliability Layer
2. Dynamic Spatial Graph Construction
3. Spatio-Temporal Feature Encoding
4. Attention-based Prediction Network
5. Multi-Pollutant Forecasting Layer

The framework jointly models:

- Spatial relationships between sensors using a dynamic graph structure,
- Temporal dependencies using gated recurrent networks,
- Pollutant interactions using attention-based fusion.

Data Preprocessing

To ensure the reliability, consistency, and learning efficiency of the proposed deep spatio-temporal framework, a structured data preprocessing pipeline is applied to all sensor measurements prior to model training and evaluation. Given that air quality sensor networks often suffer from missing values, noise, and heterogeneous scales, multiple preprocessing operations are performed to transform the raw data into high-quality spatio-temporal representations.

Training Algorithm

The model is trained using Adam optimizer with Huber loss to handle sensor noise.

Input: Sensor data X , meteorology M , graph G

Output: Predicted pollution levels Y

1. Normalize X and M
2. Construct dynamic adjacency matrix A
3. Apply GCN to X using A
4. Feed GCN output into GRU

5. Apply attention to hidden states
 6. Predict future pollutant values
 7. Compute loss
 8. Update weights
- Repeat until convergence

The Dynamic Spatial Graph Construction layer models the physical and functional relationships among sensor nodes. Unlike traditional approaches that use static adjacency matrices based solely on geographic proximity, the proposed framework constructs a dynamic graph that evolves over time based on pollution correlation, meteorological similarity, and spatial distance. Spatio-Temporal Feature Encoding is performed by combining graph-based spatial learning with sequence-based temporal modeling. In the spatial dimension, graph convolutional networks are applied over the dynamically constructed sensor graph to aggregate information from neighboring nodes in a weighted manner. The final Multi-Pollutant Forecasting Layer generates future predictions for multiple air quality indicators in a unified manner. Instead of modeling each pollutant independently, the framework performs joint multi-output regression, capturing the interdependencies among different pollutants.

Experimental Evaluation

Experiments were conducted using two publicly available benchmark datasets to validate the effectiveness and generalizability of the proposed DSTAQ-Net framework. Dataset 1 was collected by the Beijing Municipal Environmental Monitoring Center and contains hourly air quality and meteorological measurements from 36 monitoring stations between 2013 and 2017. It includes PM_{2.5}, PM₁₀, SO₂, NO₂, CO, O₃, temperature, humidity, wind speed, wind direction, and pressure.

Performance on Noisy Sensor Data

To evaluate robustness under real IoT conditions, the model was tested on the UCI Air Quality dataset.

Table 1. Performance on UCI Air Quality Dataset

Parameter	MAE	RMSE	MAPE (%)	R ²
CO	0.38	0.51	9.12	0.917
NO _x	11.92	16.04	10.36	0.902
NO ₂	8.41	12.19	9.48	0.911
Temperature	0.84	1.17	4.26	0.961
Humidity	2.91	4.28	5.87	0.946

These results confirm that DSTAQ-Net remains resilient against sensor drift and noise, making it suitable for real-world deployments.

Comparative Evaluation with Existing Methods

Table 2. Comparative Performance on PM2.5 Prediction

Model	MAE	RMSE	MAPE (%)	R ²
CNN-LSTM (Guo et al., 2023)	9.61	13.42	11.38	0.901
ST-Attention (Chen et al., 2025)	8.43	11.96	9.82	0.921
Residual ST-LSTM (Li et al., 2024)	7.98	11.14	9.21	0.934
Proposed DSTAQ-Net	7.14	10.21	8.92	0.943

The proposed framework consistently outperforms all baseline models, demonstrating superior accuracy and generalization due to its dynamic spatial modeling and attention-based learning.

Conclusion

This study presented a deep learning–based spatio-temporal framework, termed DSTAQ-Net, for accurate and reliable air quality and pollution level prediction using distributed sensor networks. The proposed framework was designed to address key limitations of existing approaches, including static spatial modeling, sensitivity to sensor noise, limited adaptability to dynamic environmental conditions, and lack of scalability for real-time smart city deployments. Comparative analysis with recent state-of-the-art spatio-temporal deep learning models from the literature showed that DSTAQ-Net outperforms existing CNN–LSTM, attention-based, and residual deep learning architectures, particularly in PM2.5 forecasting accuracy. This performance improvement can be attributed to the dynamic spatial graph modeling that adapts to changing pollutant transport patterns and the attention mechanism that selectively emphasizes the most influential sensors, pollutants, and time steps.

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Biographies



Ms. M. Divya received her Bachelor of Science (B.Sc.) degree from the University of Madras in 2010, her Master of Computer Applications (MCA) degree from the University of Madras in 2013, and her Master of Philosophy (M.Phil.) degree from St. Peter's University in 2015. She is currently working as an Assistant Professor in the Department of Bachelor of Computer Applications (BCA) and is also a Research Scholar at Thiruthangal Nadar College. Her research interests include Artificial Intelligence, Machine Learning, Deep Learning, Data Mining, Data Warehousing, and Air Quality Prediction using Machine Learning and Deep Learning techniques



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