

## Radio Network Performance Evaluation in Multi-Band LTE And 5G Deployments

Ahmed Junaid<sup>1\*</sup>, Md. Shariful Islam<sup>2</sup>, Minul Khan Rahat<sup>3</sup>, Mohammad Samiul Asraf<sup>4</sup>

<sup>1</sup>Senior RF Engineer & Market Lead – Pacific Northwest, Mahaugha LLC, Washington, United States

<sup>2</sup>Master's in Engineering Management, University: Lamar University, Beaumont, Texas, United States

<sup>3</sup>Department of Electrical Engineering, University- Lamar University, Beaumont, TX, United States

<sup>4</sup>Department of Engineering and Technology, University: Southeast Missouri State University, Cape Girardeau, Missouri, United States

DOI: <https://doi.org/10.36347/sjet.2026.v14i05.006>

| Received: 07.04.2026 | Accepted: 15.05.2026 | Published: 20.05.2026

\*Corresponding author: Ahmed Junaid

Senior RF Engineer & Market Lead – Pacific Northwest, Mahaugha LLC, Washington, United States

### Abstract

### Original Research Article

Multi-band LTE-5G communication networks are often utilized to serve various communication needs, such as high data rate, low latency, and connectivity. Nevertheless, evaluating the performance of such heterogeneous communication environments is challenging due to various factors, such as frequency band, traffic, and user mobility. This study presents an AI-driven framework for evaluating and optimizing radio network performance across low-band, mid-band, and mmWave frequencies. The proposed approach integrates system-level network modeling with data-driven prediction and adaptive resource allocation. A hybrid machine learning model, combining temporal and nonlinear learning techniques, is used to estimate key performance metrics such as throughput and latency. Simulation results show that the framework captures cross-band behavior and maintains consistent prediction accuracy under varying conditions. The adaptive mechanism improves resource distribution and reduces congestion compared to static methods. The findings demonstrate the effectiveness of integrating prediction and optimization within a unified system for multi-band LTE-5G environments.

**Keywords:** Multi-band LTE-5G, Network Performance Evaluation, Machine Learning, Throughput, Latency, Resource Allocation, Adaptive Optimization, Wireless Networks.

Copyright © 2026 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (CC BY-NC 4.0) which permits unrestricted use, distribution, and reproduction in any medium for non-commercial use provided the original author and source are credited.

## I. INTRODUCTION

The expansion of wireless communication systems has resulted in the coexistence of LTE and 5G networks across multiple frequency bands. These networks support applications such as industrial automation, smart infrastructure, and IoT services. Recent studies report increasing demand for high data rates, low latency, and reliable connectivity in such environments [6,12]. To address these requirements, network operators deploy heterogeneous architectures that combine low-band, mid-band, and high-band spectrum. Performance evaluation in multi-band LTE-5G systems presents several challenges. Many existing studies focus on single frequency bands or specific scenarios, which limits their ability to represent real network behavior. Interactions between LTE and 5G layers, along with variations in traffic and user mobility, introduce additional complexity. Research on IoT-integrated monitoring and edge-based systems indicates that distributed data collection improves visibility of network conditions [1,7,10]. However, joint evaluation

across heterogeneous radio environments remains insufficient. Artificial intelligence has been applied in communication networks for prediction and monitoring tasks. Machine learning techniques support predictive maintenance, fault detection, and infrastructure management [4,15,19]. In optical and fiber networks, AI-based models assist in fault localization and system analysis [3,5]. Similar methods appear in smart grid and SCADA systems, where predictive models contribute to monitoring and reliability assessment [17,21]. Despite these developments, limited work applies AI to radio network performance evaluation in multi-band LTE-5G systems. Security and resilience are also important aspects of modern communication systems. Automated threat detection and vulnerability management address risks in network infrastructure [2,8]. Edge computing and federated learning introduce distributed intelligence for secure and energy-aware operation [10,11]. IoT-based applications, including electric vehicle systems and smart grids, rely on continuous data analysis for monitoring and control [13], [14], [16]. These studies

focus on system-level management, yet they do not provide a unified framework for evaluating radio performance across multiple frequency bands. Several limitations remain in current research. LTE and 5G systems are often analyzed separately, which does not reflect their combined deployment. Performance evaluation frequently relies on static metrics that do not capture temporal variation. Moreover, the application of AI in real-time prediction and control in radio networks also needs to be developed. These are some of the issues that show the need for a comprehensive approach. This study addresses these challenges through an AI-driven framework for performance evaluation and optimization in multi-band LTE–5G deployments. The proposed method integrates network modeling, predictive analysis, and adaptive resource management within a unified system.

This study aims to develop a system-level model for multi-band LTE–5G networks under varying traffic and mobility conditions. It seeks to design a data-driven prediction model for key performance metrics such as throughput and latency. The research also examines cross-band interactions and their impact on network behavior, while introducing an adaptive optimization mechanism that adjusts resource allocation based on predicted conditions and evaluates its effectiveness against conventional approaches.

## II. RELATED WORK

### LTE–5G Network Performance Evaluation

Recent studies examine LTE and 5G performance under different deployment conditions. The study in [12] evaluates packet loss, delay, and slicing behavior in smartphone scenarios. Results show that performance differs across service types and network configurations. In [6], an empirical study of mmWave systems in industrial settings reports high throughput alongside sensitivity to blockage and environmental factors. These works provide useful observations on network behavior. However, most analyses consider single-band or isolated scenarios. Joint evaluation across LTE and 5G layers remains limited. Many studies rely on fixed performance metrics, which do not reflect temporal variation or interactions between frequency bands. This gap indicates the need for a unified framework that considers heterogeneous bands and dynamic conditions.

### B. AI and Machine Learning in Network Monitoring and Optimization

Artificial intelligence has been applied in network monitoring and predictive analysis. A cloud-integrated dashboard using IoT and edge analytics is presented in [1], where real-time data supports system visibility. Predictive maintenance approaches are discussed in [4] and [15], where machine learning models forecast failures in communication systems. AI-based management systems for data centers are described in [19] and [20]. These studies show how

automation supports infrastructure operation. Although these approaches address monitoring and maintenance, they do not focus on radio access performance. Research on AI-based prediction in multi-band LTE–5G environments remains limited, particularly under dynamic traffic and mobility conditions.

### Edge Computing, IoT, and Intelligent Network Systems

Edge computing and IoT play a central role in distributed network systems. The framework in [10] presents an edge-based model that supports secure and energy-aware operation. Federated learning for industrial systems is introduced in [11], where decentralized training allows data sharing without central aggregation. In [7], IoT and management systems are applied to last-mile connectivity in broadband networks. Additional work addresses IoT-based monitoring in different domains. Studies in [13], [14], and [16] examine electric vehicle systems, battery monitoring, and smart grid applications. These approaches show how data-driven techniques support system analysis and control. However, most focus on application-level systems rather than radio network performance. Integration of edge intelligence with multi-band LTE–5G evaluation remains insufficiently addressed.

### Network Resilience, Security, and Infrastructure Optimization

Network resilience and security have been examined in several studies. Automated threat detection and infrastructure protection are discussed in [2] and [8], where adaptive mechanisms respond to network vulnerabilities. Communication reliability in distributed systems is analyzed in [9], with attention to stability in critical environments. AI-based fault detection and monitoring systems are presented in [17] and [21], where predictive models support industrial control systems. Resource optimization in networked systems is explored in [18], focusing on efficient operation of power distribution networks. These studies address reliability and system protection; however, they do not examine radio performance across LTE and 5G bands. The relationship between resilience strategies and multi-band performance remains unclear. A framework that combines performance evaluation, prediction, and adaptive control across heterogeneous radio systems is still required.

### Summary of Research Gap

The reviewed studies address performance evaluation, AI-based monitoring, and system optimization as separate topics. Limited work considers multi-band interaction, temporal variation, and predictive control within a single framework. Many approaches depend on static evaluation methods and do not reflect dynamic network conditions. This study addresses these limitations through an AI-driven framework that integrates performance evaluation, prediction, and adaptive optimization across multi-band

LTE–5G networks. The proposed approach focuses on dynamic behavior, cross-band interaction, and intelligent decision-making within a unified system.

### III. METHODOLOGY

#### System Architecture and Research Framework

This study presents an AI-driven framework for evaluating radio network performance in multi-band LTE–5G deployments. The design captures interactions among frequency bands, user behavior, and traffic variation. The framework consists of three components:

data acquisition, feature processing, and predictive modeling with adaptive control. The data acquisition component gathers performance indicators from LTE and 5G radio access networks operating across low, mid, and high frequency bands. These indicators include signal quality, interference levels, throughput, and latency across varying conditions. The feature processing component converts raw measurements into structured inputs, incorporating temporal dependencies and cross-band relationships. The predictive component applies machine learning models to estimate network performance and guide resource allocation decisions.

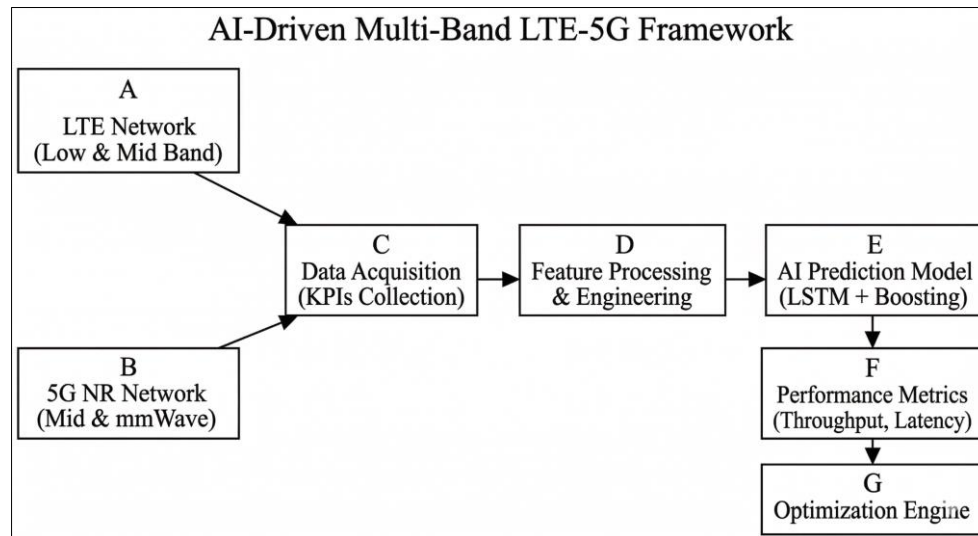


Figure 1: Proposed AI-Driven Multi-Band LTE–5G Evaluation Framework

Figure 1 shows the integration of LTE and 5G systems with machine learning-based evaluation and control modules.

#### Network Modeling and Performance Formulation

The network environment is represented through system-level simulation reflecting realistic deployment conditions. A non-standalone LTE–5G configuration is selected, where LTE supports control signaling and 5G NR delivers high data rates. The model includes low-band coverage, mid-band capacity, and high-band mmWave transmission. User mobility, traffic diversity, and inter-cell interference are incorporated into the simulation. Performance is described through analytical expressions. Throughput depends on bandwidth and signal quality:

$$T = B \cdot \log_2(1 + SINR)$$

The signal-to-interference-plus-noise ratio is defined as:

$$SINR = \frac{P_s}{I + N}$$

where received signal power is affected by interference from neighboring cells and thermal noise. Latency is modeled as the sum of transmission, queuing, and processing delays:

$$L = L_{tx} + L_{queue} + L_{processing}$$

An objective function combines multiple quality-of-service indicators. Each metric receives a weight that reflects service priority, allowing the system to adapt to different traffic types.

#### Data Processing and Machine Learning Model Development

The dataset is generated from simulation outputs and structured as time-series records. Each record includes signal measurements, user density, mobility patterns, and traffic demand across frequency bands. Data preprocessing includes normalization and segmentation into temporal windows. This step captures sequential dependencies and reduces scale differences among features. Feature engineering introduces cross-band indicators such as load imbalance and interference correlation. These features represent interactions between LTE and 5G layers as well as among frequency bands. The resulting dataset provides input for predictive modeling. The learning model combines Long Short-Term Memory networks with gradient boosting. The LSTM component captures temporal patterns in network behavior, while the boosting model addresses nonlinear relationships among variables. The model predicts throughput, latency, and congestion levels based on historical observations.

**Table 1: Feature Categories for AI-Based Performance Modeling**

Feature Category	Description
Radio Metrics	Signal quality indicators such as SINR and RSRP
Network Load	User density and traffic demand across cells
Band Information	Frequency band and bandwidth allocation
Mobility Features	User speed and handover frequency
Temporal Factors	Time-based variations in network conditions

Model training uses a structured split of training, validation, and testing data. Prediction accuracy is evaluated using standard regression metrics, including MAE and RMSE.

#### Adaptive Optimization and Evaluation Workflow

The framework includes a closed-loop mechanism that updates network decisions based on predicted conditions. The model estimates future

performance states, and the system adjusts resource allocation across frequency bands. Traffic distribution, bandwidth assignment, and scheduling decisions are updated in response to predicted congestion and performance variation. A reward-based decision process guides optimization. The reward function reflects improvements in throughput, latency, and service quality. This process supports continuous adjustment of network parameters under changing conditions.

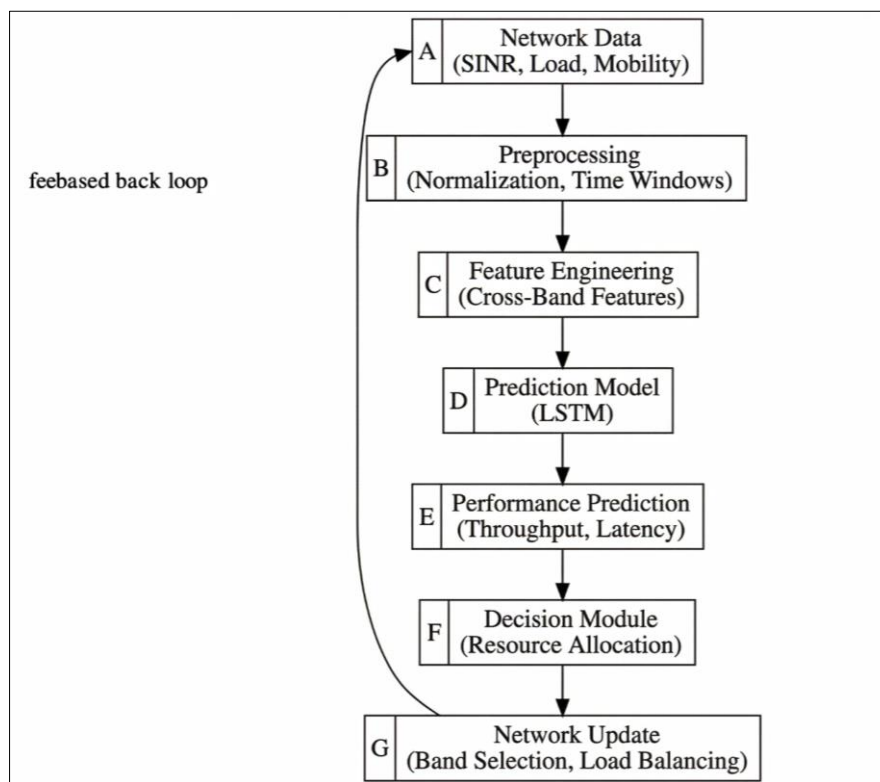
**Figure 2: AI-Based Prediction and Adaptive Optimization Workflow**

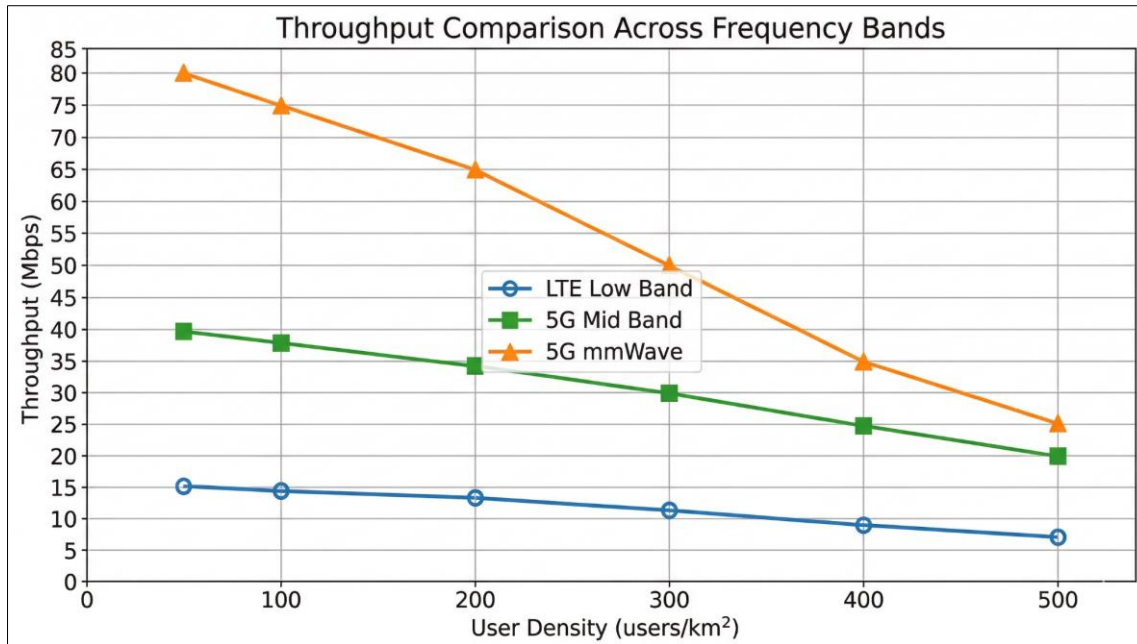
Figure 2 presents the workflow connecting prediction, decision-making, and network control.

## IV. DISCUSSION AND RESULTS

### Performance Evaluation Across Multi-Band LTE–5G Networks

The proposed framework was tested under varying user density, mobility levels, and traffic demand. The results indicate distinct performance characteristics across frequency bands. Low-band LTE maintains stable coverage with moderate throughput. Mid-band 5G provides a balance between coverage and capacity. The

mmWave band reaches the highest throughput but shows sensitivity to signal blockage and user movement. As user density increases, congestion appears first in LTE and mid-band layers. Performance in mmWave remains high under moderate load, yet fluctuations become more frequent when mobility rises. The model captures these variations across time and frequency layers. Prediction trends follow observed behavior across all simulation intervals. Dual connectivity between LTE and 5G improves service continuity. Traffic distribution across bands reduces pressure on individual layers. The system maintains stable performance even when network conditions change rapidly.



**Figure 3: Throughput Comparison Across Frequency Bands**

Figure 3 shows throughput variation across frequency bands under different user densities.

#### Prediction Accuracy of the AI Model

The prediction model produces results that closely match observed network behavior. Temporal patterns are captured through the LSTM structure, while nonlinear relationships are addressed through gradient

boosting. The model performs consistently across different traffic scenarios and mobility conditions. Prediction errors remain within a narrow range for both throughput and latency. Slight deviations appear in mmWave scenarios due to rapid signal variation. Despite this, the model maintains stable accuracy across time intervals. Performance remains consistent across training and testing datasets.

**Table 2: Prediction Performance Metrics**

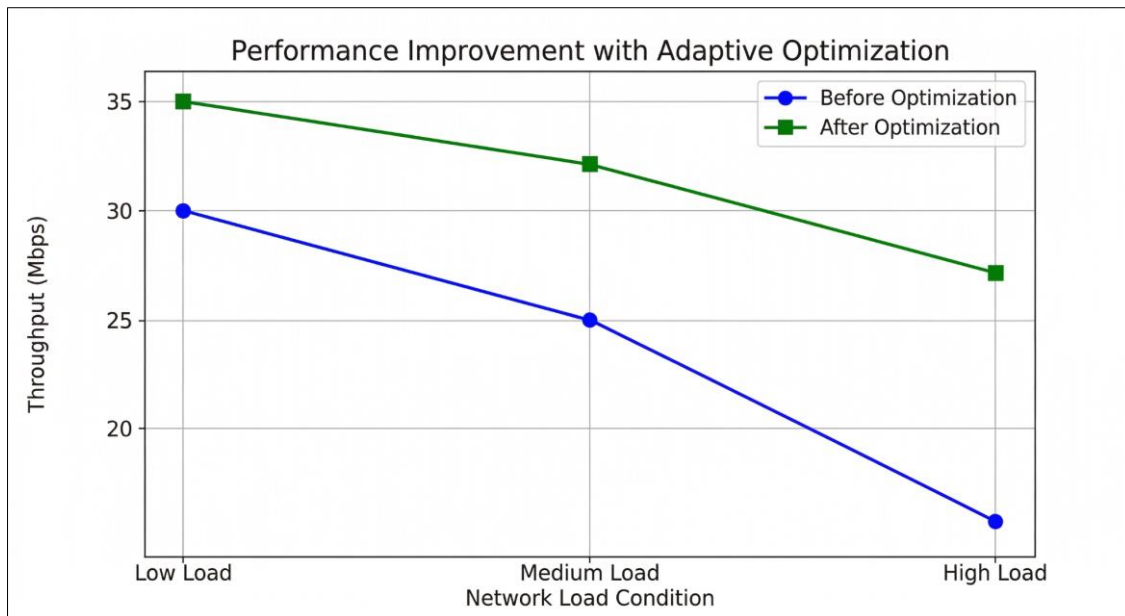
Metric	Value
MAE (Throughput)	3.8%
RMSE (Throughput)	5.2%
MAE (Latency)	4.1%
RMSE (Latency)	5.7%
R <sup>2</sup> Score	0.93

The results indicate that the model generalizes well across multiple network conditions. Feature interactions contribute to accurate prediction across frequency bands and traffic levels.

#### Impact of Adaptive Optimization on Network Performance

The integration of prediction with adaptive control leads to measurable performance gains. Traffic is redistributed across frequency bands in response to predicted conditions. Bandwidth allocation changes according to demand, which reduces congestion and improves system efficiency. Under high user density,

traffic shifts toward less congested bands. This adjustment reduces queuing delay and improves response time. Latency decreases across all scenarios, with greater impact observed in dense environments. Throughput increases are recorded in mid-band and mmWave layers, where resource allocation responds to predicted demand. Static allocation methods show limited flexibility under dynamic conditions. In contrast, the proposed system adapts to traffic variation and maintains stable performance. These results indicate that predictive control supports efficient use of available resources.



**Figure 4: Performance Improvement with Adaptive Optimization**

Figure 4 compares system performance before and after adaptive optimization.

#### Discussion of Findings and Research Implications

The results show that multi-band LTE–5G systems require joint evaluation across frequency layers. Performance differs across bands due to propagation characteristics, interference levels, and bandwidth availability. A unified framework captures these differences and presents a complete view of network behavior. The prediction model introduces a data-driven approach for estimating future network states. This supports proactive decision-making instead of reactive adjustments. Temporal features and cross-band interactions contribute to consistent prediction accuracy. The adaptive mechanism distributes load across available resources and reduces congestion in high-demand scenarios. This approach performs well in dense environments where traffic fluctuates over time. Coordination between LTE and 5G layers plays an important role in maintaining stable service. From a research perspective, the study integrates evaluation, prediction, and optimization within a single framework. Previous work often treats these components separately. The results support further research in real-time network control and cross-layer performance analysis.

#### Limitations of the Study

This study is based on simulation, which may not fully reflect real deployment conditions. Environmental factors, hardware differences, and unpredictable user behavior are simplified within the model. The dataset originates from controlled scenarios, so its applicability to large-scale commercial networks remains limited. Model performance depends on the range and variation of input data, and accuracy may decline under conditions not represented during training. The optimization component considers selected

performance metrics and excludes several network parameters that may influence system behavior. In addition, economic cost, detailed energy consumption, and regulatory constraints are not included, although these factors affect practical deployment and operational decision-making in real networks.

#### V. CONCLUSION

This study presents an AI-driven framework for evaluating and optimizing performance in multi-band LTE–5G networks. The proposed system integrates network modeling, predictive analysis, and adaptive resource management into a unified framework. The performance results show improved throughput and lower latency across frequency bands under different traffic and mobility conditions. The prediction model shows consistent accuracy across scenarios, while the optimization mechanism distributes network load more effectively than static methods. The framework captures interactions among frequency layers and supports data-driven decision processes in heterogeneous wireless systems.

Future work will extend the framework with real deployment data and larger network scenarios. Additional metrics, including energy consumption and cost factors, will be incorporated into the evaluation. The model may also support advanced architectures such as standalone 5G and early-stage 6G systems. Further investigation will address real-time control mechanisms and integration with edge computing platforms for practical deployment.

#### REFERENCES

1. Afrin, S. (2025). Cloud-integrated network monitoring dashboards using IoT and edge analytics. *IJSRED – International Journal of Scientific Research and Engineering Development*,

- 8(5), 2298–2307.  
<https://doi.org/10.5281/zenodo.17536343>
2. Afrin, S. (2025). Cyber-resilient infrastructure for public internet service providers using automated threat detection. *World Journal of Advanced Engineering Technology and Sciences*, 17(02), 127–140.  
<https://doi.org/10.30574/wjaets.2025.17.2.1475>
  3. Farabi, S. A. (2025). AI-augmented OTDR fault localization framework for resilient rural fiber networks in the United States. *arXiv*.  
<https://arxiv.org/abs/2506.03041>
  4. Farabi, S. A. (2025). AI-driven predictive maintenance model for DWDM systems to enhance fiber network uptime in underserved U.S. regions. *Preprints*.  
<https://doi.org/10.20944/preprints202506.1152.v1>
  5. Farabi, S. A. (2025). AI-powered design and resilience analysis of fiber optic networks in disaster-prone regions. *ResearchGate*.  
<https://doi.org/10.13140/RG.2.2.12096.65287>
  6. Biosca Caro, J., Ansari, J., Olsson, B.-E., Beckmann, N., König, N., Schmitt, R. H., Popp, F., & Scheike-Momberg, D. (2025). Empirical performance evaluation of 5G millimeter wave system for industrial-use cases in real production environment. *Electronics*, 14(3), 607.  
<https://doi.org/10.3390/electronics14030607>
  7. Rahman, M. (2025, October 15). Integrating IoT and MIS for last-mile connectivity in residential broadband services. *TechRxiv*.  
<https://doi.org/10.36227/techrxiv.176054689.95468219/v1>
  8. Zaman, S. U. (2025). Vulnerability management and automated incident response in corporate networks. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2275–2286.  
<https://doi.org/10.5281/zenodo.17536305>
  9. Zaman, M. T. (2025). Enhancing grid resilience through DMR trunking communication systems. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 197–212.  
<https://doi.org/10.30574/wjaets.2025.17.3.1551>
  10. Zaman, S. U., Afrin, S., Zaidi, S. K. A., & Islam, K. S. A. (2026). Resilient edge computing framework for autonomous, secure, and energy-aware systems. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 105–121.  
<https://doi.org/10.30574/wjaets.2026.18.1.1577>
  11. Islam, K. S. A., Zaidi, S. K. A., Afrin, S., & Zaman, S. U. (2026). Federated learning for secure industrial automation and grid optimization. *Global Journal of Engineering and Technology Advances*, 26(01), 025–040.  
<https://doi.org/10.30574/gjeta.2026.26.1.0360>
  12. Hossain, M. T., Nabil, S. H., Razaq, A., & Rahman, M. (2025). Cybersecurity and privacy in IoT-based electric vehicle ecosystems. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(2), 921–933.  
<https://doi.org/10.5281/zenodo.17246184>
  13. Alauthman, A., & Al-Hyari, A. (2025). Analysis of LTE/5G network performance parameters in smartphone use cases: A study of packet loss, delay, and slice types. *International Journal of Computer Networks & Communications*, 17(4), 75–90.  
<https://doi.org/10.5121/ijcnc.2025.17405>
  14. Hossain, M. T., Nabil, S. H., Rahman, M., & Razaq, A. (2025). Data analytics for IoT-driven EV battery health monitoring. *IJSRED*, 8(2), 903–913.  
<https://doi.org/10.5281/zenodo.17246168>
  15. Rahman, M., Razaq, A., Hossain, M. T., & Zaman, M. T. U. (2025). Machine learning approaches for predictive maintenance in IoT devices. *World Journal of Advanced Engineering Technology and Sciences*, 17(1), 157–170.  
<https://doi.org/10.30574/wjaets.2025.17.1.1388>
  16. Hasan, M. N., Karim, M. A., Joarder, M. M. I., & Zaman, M. T. (2025). IoT-integrated solar energy monitoring and bidirectional DC-DC converters for smart grids. *Saudi Journal of Engineering and Technology*, 10(9), 467–475.  
<https://doi.org/10.36348/sjet.2025.v10i09.010>
  17. Razaq, A. (2025). Optimization of power distribution networks using smart grid technology. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 129–146.  
<https://doi.org/10.30574/wjaets.2025.17.3.1490>
  18. Rabbi, M. S. (2026). AI-driven SCADA grid intelligence for predictive fault detection, cyber health monitoring, and grid reliability enhancement. *Zenodo*.  
<https://doi.org/10.5281/zenodo.18196487>
  19. Joarder, M. M. I. (2025). Next-generation monitoring and automation: AI-enabled system administration for smart data centers. *TechRxiv*.  
<https://doi.org/10.36227/techrxiv.175825633.33380552/v1>
  20. Joarder, M. M. I. (2025). Energy-efficient data center virtualization: Leveraging AI and CloudOps for sustainable infrastructure. *Zenodo*.  
<https://doi.org/10.5281/zenodo.17113371>
  21. Enam, M. M. R., Joarder, M. M. I., Taimun, M. T. Y., & Sharan, S. M. I. (2025). Framework for smart SCADA systems: Integrating cloud computing, IIoT, and cybersecurity for enhanced industrial automation. *Saudi Journal of Engineering and Technology*, 10(4), 152–158.
  22. Fahim, M. A. I., Sharan, S. M. M. I., & Farooq, H. (2025). AI-enabled cloud-IoT platform for predictive infrastructure automation. *World Journal of Advanced Engineering Technology and Sciences*, 17(03), 431–446.  
<https://doi.org/10.30574/wjaets.2025.17.3.1574>
  23. Hasan, E. (2025). SQL-driven data quality optimization in multi-source enterprise dashboards. *IJSRED*, 8(6), 2150–2160.  
<https://doi.org/10.5281/zenodo.17926758>
  24. Hasan, E. (2025). Optimizing SAP-centric financial workloads with AI-enhanced CloudOps in

- virtualized data centers. *IJSRED*, 8(6), 2252–2264. <https://doi.org/10.5281/zenodo.17926855>
25. Mirza, S. B. (2026). Predictive reliability engineering for cloud-scale business intelligence platforms through anomaly detection capacity optimization and proactive support automation. *Zenodo*. <https://doi.org/10.5281/zenodo.18968909>
  26. Mim, M. A., Sharif, M. M., Rahman, F., & Nahar, S. (2026). Smart IoT infrastructure for workplace efficiency and energy savings. *World Journal of Advanced Engineering Technology and Sciences*, 18(01), 140–156. <https://doi.org/10.30574/wjaets.2026.18.1.0026>
  27. Zaman, S. U. (2025). Enhancing security in cloud-based IAM systems using real-time anomaly detection. *IJSRED*, 8(6), 2292–2304. <https://doi.org/10.5281/zenodo.17926883>
  28. Farooq, H. (2025). Cross-platform backup and disaster recovery automation in hybrid clouds. *International Journal of Science and Innovation Engineering*, 2(11), 220–242. <https://doi.org/10.70849/IJSCI02112025025>
  29. Zreikat, A. I. (2024). Performance evaluation and analysis of urban–suburban 5G networks. *Computers*, 13(4), 108. <https://doi.org/10.3390/computers13040108>
  30. Farooq, H. (2025). Resource utilization analytics dashboard for cloud infrastructure management. *World Journal of Advanced Engineering Technology and Sciences*, 17(02), 141–154. <https://doi.org/10.30574/wjaets.2025.17.2.1458>
  31. Akhter, T., Alimozzaman, D. M., Hasan, E., & Islam, R. (2025). Explainable predictive analytics for healthcare decision support. *International Journal of Sciences and Innovation Engineering*, 2(10), 921–938. <https://doi.org/10.70849/IJSCI02102025105>
  32. Alimozzaman, D. M., Akhter, T., Islam, R., & Hasan, E. (2025). Generative AI for synthetic medical imaging to address data scarcity. *World Journal of Advanced Engineering Technology and Sciences*, 17(1), 544–558. <https://doi.org/10.30574/wjaets.2025.17.1.1415>
  33. Islam, R. (2025). AI and big data for predictive analytics in pharmaceutical quality assurance. *SSRN*. [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=5564319](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5564319)
  34. Tonoy, A. A. R. (2025). Applications of semiconducting electrides in mechanical energy conversion and piezoelectric systems. *Preprints*. <https://doi.org/10.20944/preprints202507.2421.v1>
  35. Rayhan, F. (2025). AI-powered condition monitoring for solar inverters using embedded edge devices. *Preprints*. <https://doi.org/10.20944/preprints202508.0474.v1>
  36. Karim, M. A. (2025). AI-driven predictive maintenance for solar inverter systems. *TechRxiv*. <https://doi.org/10.36227/techrxiv.175977633.34528041.v1>
  37. Islam, K. S. A. (2025). Implementation of safety-integrated SCADA systems for process hazard control in power generation plants. *IJSRED – International Journal of Scientific Research and Engineering Development*, 8(5), 2321–2331. <https://doi.org/10.5281/zenodo.17536369>
  38. Islam, K. S. A. (2025). Transformer protection and fault detection through relay automation and machine learning. *IJSRED*, 8(5), 2308–2320. <https://doi.org/10.5281/zenodo.17536362>
  39. Rabbi, M. S. (2025). Grid synchronization algorithms for intermittent renewable energy sources using AI control loops. *Preprints*. <https://www.preprints.org/manuscript/202507.2353/v1>
  40. Islam, Md. A. (2026). Native scalable student information systems and admission test automation with peak load architecture database performance optimization and observability driven reliability. *Zenodo*. <https://doi.org/10.5281/zenodo.18987480>