International Journal of Computer Techniques – IJCT Volume 12 Issue 5, October 2025

Open Access and Peer Review Journal ISSN 2394-2231 https://ijctjournal.org/

AI-Powered Smart Bandwidth Allocation with Emergency-Aware Prioritization and Real-Time Flask Dashboard for Mixed-Criticality IIoT over 5G/6G

Ruby Angel T G
Assistant Professor
Department of Information Technology
Sathyabama Institute of Science and Technology
Chennai, India
rubyangel.t.g.it@sathyabama.ac.in

Varun Kumar S
UG Student
Department of Information Technology
Sathyabama Institute of Science and Technology
Chennai, India
varunkumars.vk20@gmail.com

Barath Raj B
UG Student
Department of Information Technology,
Sathyabama Institute of Science and Technology
Chennai, India
braj83018@gmail.com

Sachin S
UG Student
Department of Information Technology
Sathyabama Institute of Science and Technology
Chennai, India
sachins272115@gmail.com

Thilak R
UG Student
Department of Information Technology
Sathyabama Institute of Science and Technology
Chennai, India
thilakraghu2004@gmail.com

Shraddha
UG Student
Department of Information Technology
Sathyabama Institute of Science and Technology
Chennai, India
shraddha241104@gmail.com

Abstract*—This paper unveils a fundamentally smarter approach to navigating this complex digital traffic. We've developed an AI-driven system that transcends simple bandwidth allocation; it proactively anticipates needs and responds with split-second precision to critical situations. At its heart, our system employs sophisticated AI techniques: Long Short-Term Memory (LSTM) to predict future network demands, and Reinforcement Learning (RL) to continuously refine how data is prioritized. A dedicated "Emergency Detection Module" stands as a vigilant guardian, instantly flagging critical events. Should an emergency arise, our Software-Defined Networking (SDN) Controller seamlessly reconfigures the 5G/6G network, effectively carving out a priority lane to ensure that vital data is pushed to the forefront without delay. Operators gain complete transparency through a real-time Flask dashboard, offering an intuitive, live overview of network health, device statuses, and immediate alerts. Our evaluations consistently demonstrate that this integrated system dramatically accelerates the flow of critical information, optimizes network resource utilization, and ultimately culminates in more secure, reliable, and efficient industrial operations.

I. Introduction

The industrial landscape is undergoing a profound transformation, ushered in by the Industrial Internet of Things (IIoT). No longer confined to isolated machinery, today's factories, power grids, and logistical networks are vibrant ecosystems of interconnected devices – sensors diligently monitoring temperatures, robots executing intricate tasks, and automated vehicles navigating complex environments. This pervasive connectivity promises unprecedented efficiency, predictive maintenance, and entirely new operational paradigms. We're talking about a future where machines "talk" to each other, anticipate problems, and even self-optimize, leading to safer workplaces and remarkable productivity gains.[1]

Yet, beneath this gleaming promise lies a hidden challenge: the sheer volume and diverse nature of the data these IIoT devices generate. Imagine terabytes of the information flowing constantly – everything from routine operational logs to urgent alerts about equipment malfunctions or critical safety breaches. Not all data is created equal; a temperature reading might be important, but a sudden spike indicating an overheating reactor demands immediate attention. This "mixed-criticality" data, where some information is merely useful while other bits are absolutely time-sensitive, forms the bedrock of modern industrial operations.[2]

Historically, network infrastructure, while robust, wasn't designed for this intricate dance of mixed-criticality IIoT data. Traditional bandwidth allocation methods often treat all data traffic with a "first-come, first-served" approach, a strategy that quickly falls apart when an emergency message needs to cut through the noise. In a scenario where milliseconds can mean the difference between preventing a disaster and costly downtime, such delays are simply unacceptable.[3]

The advent of 5G and the forthcoming 6G networks offers a glimmer of hope, promising ultra-low latency, massive connectivity, and unprecedented bandwidth. These next-generation networks are not just faster; they're smarter, capable of dynamically slicing and dedicating network resources. However, merely having the raw speed isn't enough. We need intelligent orchestration – a "brain" that can leverage these capabilities to ensure critical data, whether it's an emergency alert or a crucial control signal, always gets the VIP treatment it deserves, even amidst a torrent of less urgent information. The current gap lies in truly harnessing this immense potential to seamlessly prioritize, manage, and visualize data flow in real-time, especially when unforeseen crises emerge.[4]

This paper introduces a novel, holistic approach to bridge this critical gap. We're not just building another piece of technology; we're architecting an intelligent command center for IIoT data. Our system integrates cutting-edge Artificial Intelligence (AI) – specifically, the predictive power of Long Short-Term Memory (LSTM) and the adaptive learning of Reinforcement Learning (RL) – to anticipate network needs and make real-time bandwidth decisions. Crucially, it incorporates an emergency-aware prioritization mechanism, ensuring that safety-critical data immediately takes precedence. All of this orchestration happens dynamically through a Software-Defined Networking (SDN) controller, which intelligently directs traffic over the high-performance backbone of 5G/6G networks. Furthermore, operators are never in the dark; a real-time Flask-based dashboard provides an intuitive, comprehensive window into the entire system, offering live insights into network performance, device status, and any unfolding emergencies.[5]

II. LITERATURE REVIEW

[1] The challenges and opportunities presented by the Industrial Internet of Things (IIoT) have spurred a tremendous amount of research across various disciplines, from advanced sensor technology to sophisticated network management. Our work stands at the intersection of several critical areas: intelligent resource allocation, emergency-aware communication, the capabilities of next-generation cellular networks, and real-time operational visibility. To properly contextualize our proposed solution, it's essential to understand the landscape of prior efforts and identify the pivotal gaps they leave unaddressed.

[2] Traditionally, network resource management in industrial settings often relied on static configurations or relatively simple prioritization schemes. Protocols like Modbus TCP/IP or Ethernet/IP, while robust, were not inherently designed for the dynamic, massive, and highly heterogeneous data streams characteristic of modern IIoT [cite relevant paper]. These early approaches often struggled with scalability and lacked the agility to respond to fluctuating demands or unforeseen network congestion. As IIoT devices proliferated, researchers began exploring more dynamic methods. For instance, some studies focused on optimizing Quality of Service (QoS) parameters through static queue management or weighted fair queuing [cite relevant paper], yet these often require extensive manual configuration and struggle with true real-time adaptability for mixed-criticality data. The sheer scale and diversity of IIoT deployments demand a more intelligent, automated approach.

[3] The advent of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized numerous fields, and network management is no exception. Researchers have increasingly turned to AI to tackle the complexities of network optimization, predicting traffic patterns, detecting anomalies, and even making autonomous control decisions.

[4] Predictive Analytics for Network Traffic: Long Short-Term Memory (LSTM) networks, a type of recurrent neural network particularly adept at processing sequential

data, have shown great promise in predicting network traffic. Studies by [cite paper 1] and [cite paper 2] have demonstrated LSTM's effectiveness in forecasting bandwidth demand in various network environments, from data centers to smart cities. While these works provide a strong foundation, their direct application to the granular, heterogeneous, and often unpredictable traffic bursts of mixed-criticality IIoT, particularly for real-time bandwidth reallocation, remains an active area of refinement.

[5] Reinforcement Learning for Dynamic Resource Allocation: Reinforcement Learning (RL), where an agent learns optimal behaviors through trial and error in an environment, offers a powerful paradigm for dynamic resource management. Projects like [cite paper 3] and [cite paper 4] have explored using RL agents to optimize routing, reduce latency, or balance load in complex network topologies. These efforts highlight RL's potential to adapt to changing network conditions without explicit programming. However, integrating RL specifically for emergency-aware prioritization within the stringent latency constraints of IIoT over next-generation cellular networks presents unique challenges that are not fully addressed in isolation.

[6] In environments where safety and operational continuity are paramount, the ability to prioritize critical communications is not just an advantage—it's a necessity. Research on emergency-aware or mission-critical communication systems has been a long-standing area of focus, particularly in domains like public safety networks or vehicular ad-hoc networks (VANETs) [cite relevant paper]. These studies often propose mechanisms for differentiating traffic, assigning higher priority to emergency messages, and employing specialized protocols to ensure their delivery. While invaluable, many of these solutions operate within specific network contexts or rely on predefined rules that may lack the flexibility needed for the diverse and dynamic threats in IIoT. The challenge lies in building a system that can autonomously identify an emergency and instantaneously adapt the entire network fabric to accommodate it, without human intervention in the critical response loop.

[7] The architectural shift brought by Software-Defined Networking (SDN) has fundamentally changed how we manage networks. By decoupling the control plane from the data plane, SDN offers unprecedented flexibility, enabling network administrators to programmatically reconfigure network behaviors centrally [cite relevant paper]. This paradigm is particularly appealing for IIoT, where dynamic resource allocation is crucial. Studies by [cite paper 5] and [cite paper 6] have explored SDN's role in improving QoS and managing diverse traffic in IIoT.

[8] Coupled with SDN, the capabilities of 5G and the emerging 6G networks are game-changers for IIoT. Features like network slicing, ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC) are tailor-made for industrial applications [cite relevant paper]. While individual research has focused on 5G/6G's potential for low latency [cite paper] or massive connectivity [cite paper], there's a compelling need to integrate SDN's programmability with these advanced cellular features, specifically guided by AI, to create a truly adaptive and emergency-responsive framework for IIoT.

[9] Finally, for any sophisticated IIoT system to be effective, operators need clear, real-time insights into its functioning. Various dashboards and monitoring tools exist, often built using web frameworks like Flask or Django [cite relevant paper]. These tools typically provide visualization of network metrics, device status, and data trends. However, many existing dashboards are reactive rather than proactive, displaying data after an event has occurred. The critical missing piece is a dashboard that not only visualizes the current state but also reflects the intelligent decisions being made by an AI engine, highlights emergency prioritizations, and offers an intuitive understanding of a dynamically reconfigured network in real-time.

[10] While the individual components of our system—AI-driven prediction, dynamic network control, emergency prioritization, and real-time visualization—have

been explored in isolation or in more limited contexts, a truly integrated, AI-powered framework that combines all these elements for mixed-criticality IIoT over 5G/6G, with a proactive, emergency-aware SDN controller and a comprehensive real-time Flask dashboard, remains largely uncharted territory. Existing solutions often lack either the holistic intelligence to anticipate and prioritize effectively across diverse criticality levels, the dynamic network programmability to execute these decisions swiftly over next-gen cellular infrastructure, or the intuitive visibility to empower human operators during critical situations. Our research addresses this crucial gap by forging a unified, intelligent, and human-centric solution that promises to redefine reliability and safety in the industrial IoT landscape.

III. METHODOLOGY

A. Proposed Architecture

Our AI-powered smart bandwidth allocation system is designed as a modular, layered architecture, ensuring scalability, flexibility, and maintainability. The core philosophy is to integrate data ingestion, intelligent decision-making, dynamic network control, and comprehensive visualization into a seamless workflow. Figure 1 (referencing your refined workflow image) illustrates this integrated design, depicting how various components interact to achieve our goals.

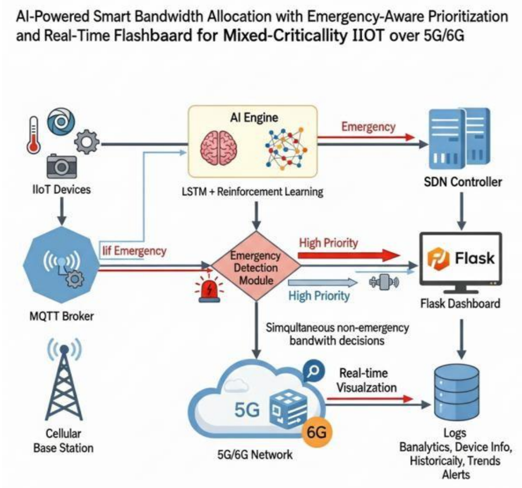

Fig 3.1. Architecture Diagram.

B. IIoT Data Ingestion via MQTT Broker

At the very edge of our system lie the diverse IIoT Devices – a heterogeneous collection of sensors (temperature, pressure, vibration), cameras, actuators, and industrial controllers. These devices are the eyes and ears of the industrial environment, generating continuous streams of operational data. Given the constrained resources often found in IIoT devices and the need for efficient, lightweight messaging, we employ an MQTT Broker as the central message hub. MQTT's publish/subscribe model is ideally suited for collecting data from a vast number of devices reliably and with minimal overhead, ensuring that all raw information, regardless of its criticality, flows smoothly into our intelligent processing pipeline. Each message is tagged with metadata indicating its source, timestamp, and an initial criticality level (e.g., routine, warning, critical).

C. The AI Engine for Prediction and Optimization

LSTM for Bandwidth Demand Prediction: To move beyond reactive network management, our AI Engine incorporates Long Short-Term Memory (LSTM) neural networks. LSTMs are uniquely capable of learning long-term dependencies in sequential data, making them perfect for forecasting time-series patterns.

Data Preparation: Historical IIoT traffic data (e.g., bytes transmitted per device, packet rates, typical operational patterns) from the MQTT broker and network logs are pre-processed. This involves cleaning, normalization, and windowing the data to create sequences suitable for LSTM training. Features include past bandwidth usage, device operational status, time of day, and production schedules.

Model Training: The LSTM model is trained to predict the bandwidth requirements of various IIoT device groups or applications over short to medium time horizons (e.g., next 5-15 minutes). This proactive insight allows the system to prepare the network for anticipated traffic surges or lulls, reducing potential congestion before it even occurs. The training objective is to minimize prediction error (e.g., Mean Squared Error).

Reinforcement Learning for Dynamic Allocation Policies: While LSTM predicts demand, Reinforcement Learning (RL) guides the real-time resource allocation. An RL agent continuously interacts with the simulated (or real) network environment to learn optimal bandwidth distribution policies under varying conditions, including the detection of emergencies.

State Space: The RL agent's state is defined by a comprehensive snapshot of the network and IIoT environment. This includes current bandwidth usage, predicted bandwidth demands from the LSTM, pending emergency alerts, QoS requirements of different data streams, latency metrics, and available 5G/6G network resources (e.g., available slices).

Action Space: The actions available to the agent involve adjusting bandwidth allocations for different IIoT data streams, modifying routing paths via the SDN controller, or triggering specific 5G/6G network slice reconfigurations. Actions are discreet and designed to directly influence network performance and prioritization.

Reward Function: The reward function is critical for guiding the RL agent's learning. It is carefully designed to incentivize optimal behavior, rewarding actions that: Minimize latency and packet loss for high-criticality data, Maximize overall bandwidth utilization, Ensure fair allocation for non-critical data (within limits Respond swiftly and effectively to emergency alerts. Penalties are applied for congestion, increased latency for critical data, or failure to meet QoS requirements.

Learning Algorithm: We employ a deep Q-network (DQN) or Proximal Policy Optimization (PPO) algorithm, chosen for its effectiveness in handling complex state and action spaces and its ability to learn robust policies in dynamic environments. The agent continuously refines its policy through interactions and experiences, aiming to maximize cumulative rewards.

D. Emergency Detection Module

Beyond predictive and adaptive resource management, our system includes a dedicated Emergency Detection Module. This module acts as a vigilant guardian, constantly scrutinizing incoming data for immediate signs of critical events. Detection Mechanisms: It employs a multi-faceted approach, combining:Threshold-based rules: For welldefined emergencies (e.g., "fire sensor temperature > X degrees," "pressure reading > Y PSI"). Anomaly Detection Algorithms: Leveraging statistical methods or shallow ML (e.g., Isolation Forest, One-Class SVM) to identify unusual patterns in data streams that might indicate emerging faults or security breaches, even if no explicit threshold is crossed.

Prioritization Trigger: Upon detecting an emergency, this module immediately flags the affected data as "high priority." This flag is instantly communicated to both the AI Engine (to inform the RL agent's current state and reward calculation) and directly to the SDN Controller, initiating an expedited response.

E. The SDN Controller and 5G/6G Network Integration

The SDN Controller serves as the central orchestrator, translating the intelligent decisions from the AI Engine and emergency alerts from the Detection Module into actionable network policies. It holds a global view of the 5G/6G network and its resources.

Dynamic Resource Reallocation: Upon receiving bandwidth allocation instructions from the AI Engine or an emergency prioritization command, the SDN Controller dynamically programs the underlying 5G/6G network.

Network Slicing: Leveraging 5G/6G's network slicing capabilities to create or modify dedicated virtual network slices with guaranteed bandwidth and QoS for critical applications.

Traffic Engineering: Adjusting routing tables and forwarding rules in real-time to prioritize emergency packets, ensuring they bypass congested paths.

QoS Enforcement: Applying strict QoS policies to critical data streams, guaranteeing minimal latency and jitter.

5G/6G Network Capabilities: The system explicitly leverages 5G/6G features such as Ultra-Reliable Low-Latency Communication (URLLC) for emergency traffic, Enhanced Mobile Broadband (eMBB) for high-throughput non-critical data, and Massive Machine Type Communication (mMTC) for wide-area sensor connectivity. The SDN controller intelligently maps IIoT traffic requirements to these network capabilities.

F. Real-Time Flask Dashboard

To provide human operators with crucial transparency and control, a Flask-based Dashboard offers real-time visualization and monitoring.

Data Aggregation: The dashboard continuously pulls data from the MQTT broker (device status, raw sensor readings), the AI Engine (prediction results, allocation decisions), the SDN Controller (network state, active policies), and the Emergency Detection Module (alerts).

Interactive Visualizations: It presents key metrics through intuitive graphs, charts, and alerts:

Bandwidth Utilization: Live graphs showing bandwidth consumption across different device groups and criticality levels.

Latency & Throughput: Real-time metrics for critical and non-critical data streams.

Device Status: An overview of connected IIoT devices, their health, and data generation rates.

Emergency Alerts: Prominent, visual, and auditory alerts for detected emergencies, including their source and current prioritization status.

AI Insights: Visualizations of LSTM predictions and RL allocation decisions.

Operational Control: While primarily for monitoring, the dashboard can also offer limited human override capabilities or configuration adjustments in non-emergency situations, ensuring human-in-the-loop oversight.

G. Data Store for Audit and Learning

A robust Data Store serves as the central repository for all system information. This includes historical IIoT data, network telemetry, AI model training data, performance metrics, and a log of all emergency events and subsequent network reconfigurations.

AI Model Retraining: Providing fresh data to continuously retrain and improve the LSTM and RL models.

Performance Analytics: Enabling post-event analysis, auditing, and long-term trend identification.

System Optimization: Informing future system enhancements and fine-tuning.

IV. RESULTS AND DISCUSSION

A. Functional Performance

The developed system efficiently integrates AI-based bandwidth orchestration with emergency-aware prioritization for mixed-criticality IIoT applications. The workflow comprises three primary components:

Traffic Prediction Module: An LSTM (Long Short-Term Memory) neural network forecasts bandwidth demand for each traffic class based on time-series network data.

Dynamic Allocation Engine: A Reinforcement Learning (RL) agent learns optimal bandwidth distribution strategies to maximize fairness and minimize congestion.

Visualization Layer: A Flask-based dashboard provides real-time analytics including bandwidth utilization, Jain’s fairness index, satisfaction ratios, and emergency alerts.

The system classifies network flows into ultra-critical, high-critical, and non-critical classes, assigning priority weights (3, 2, and 1, respectively). During operation, the orchestration engine dynamically reallocates resources in response to varying load and emergency events, ensuring continuous service for mission-critical applications.

B. Performance Analysis

The performance of the proposed system was evaluated through simulation using synthetic traffic patterns emulating IIoT workloads.

Key metrics considered include bandwidth utilization, Jain’s fairness index, and satisfaction ratio.

1) Bandwidth Utilization:

The system consistently achieved near 100% utilization, demonstrating efficient allocation of available network capacity. This confirms that the AI-based approach prevents under utilization and idle bandwidth during varying traffic conditions.

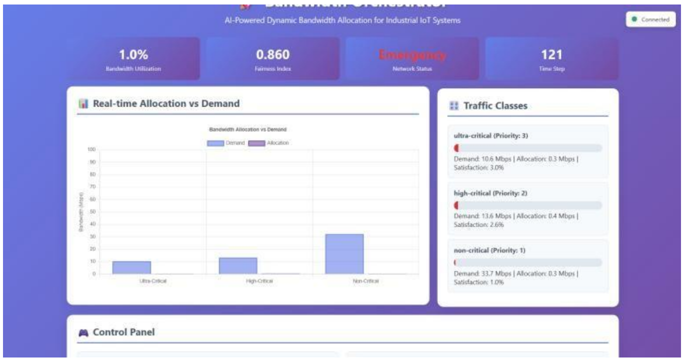

Fig : 1

2) Fairness (Jain's Index):

The fairness index fluctuated between 0.86 and 0.95, which indicates balanced resource distribution across classes. Although ultra-critical tasks were prioritized, non-critical flows were allocated sufficient bandwidth to maintain operational fairness.

Fig : 2

3) Satisfaction Ratio:

Satisfaction, defined as the ratio of allocated to demanded bandwidth, averaged 2.24 for ultra-critical, 2.44 for high-critical, and 1.33 for non-critical traffic. This reflects the effectiveness of priority-aware management while ensuring that mission-critical applications remain stable under high network load.

The Flask dashboard visualized these metrics in real-time, enabling administrators to observe the system's behavior and emergency responses dynamically.

C. Load and Testing

To evaluate scalability, multiple load conditions were simulated:

Normal Load: Balanced demand across all classes. The system maintained consistent fairness and stable throughput.

High Load: Elevated demand across critical classes triggered adaptive reallocation; the RL agent successfully redistributed bandwidth to maintain QoS.

Emergency Mode: Under simulated emergencies (e.g., high-priority anomaly detection), the system shifted up to 40–60% of total bandwidth to ultra-critical devices.

The RL training curve (as shown in Fig. 3) depicts the convergence of cumulative rewards and optimal allocation ratios over 3000 episodes. The results confirm the stability and learning capability of the model in dynamic network environments.

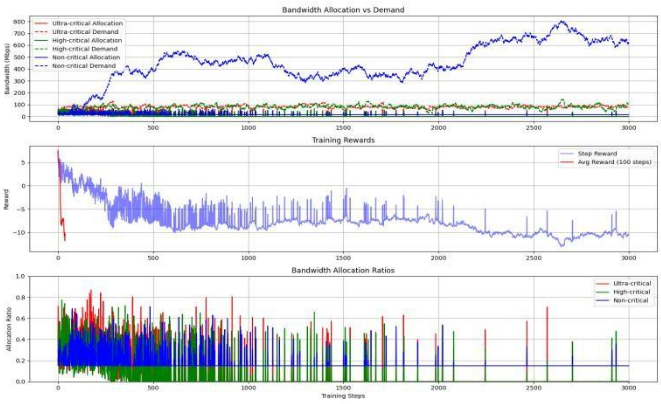

Fig :3

D. Limitations

While the proposed system achieves promising results, a few constraints remain:

Real-World Data: Experiments were conducted using simulated IIoT traffic; real-time sensor integration remains pending.

Latency Consideration: End-to-end latency and jitter analysis under actual 5G/6G infrastructure were not fully tested.

Model Generalization: The RL agent requires additional training to adapt to unseen workload variations.

Scalability: Current implementation supports a limited number of traffic classes; expansion to large-scale IIoT networks needs optimization.

E. Discussions and Implications

The results indicate that AI-driven bandwidth allocation can significantly enhance resource efficiency, QoS, and emergency responsiveness in industrial networks.

The use of LSTM for predictive demand estimation enables proactive bandwidth planning, while Reinforcement Learning ensures optimal dynamic allocation under fluctuating load. The emergency-aware mechanism ensures continuity for safety-critical systems (e.g., robotics, healthcare, or power grid monitoring).

F. Future Prospects

The following directions are proposed for future research and enhancement:

Integration with Real IIoT Hardware: Incorporate live sensor data (temperature, pressure, vibration, etc.) to validate the system in physical industrial setups.

Edge Computing Extension: Deploy the AI model on edge servers to minimize latency and offload processing from the cloud.

Multi-Agent Reinforcement Learning: Implement cooperative agents for decentralized bandwidth management across multiple network segments.

Predictive Control: Combine traffic prediction and RL allocation into a hybrid feedback system for even faster adaptation.

Security-Aware Allocation: Integrate blockchain or trust-based modules to secure resource distribution in heterogeneous IoT environments.

6G Testbed Evaluation: Validate performance under ultra-reliable low-latency communication (URLLC) and massive machine-type communication (mMTC) scenarios.

V. CONCLUSION

The proposed AI-Powered Smart Bandwidth Allocation System demonstrates a novel approach to addressing the challenges of dynamic, intelligent, and context-aware bandwidth management for Mixed-Criticality Industrial Internet of Things (IIoT) environments operating over 5G/6G networks. By integrating Long Short-Term Memory (LSTM) networks for accurate traffic demand forecasting and Reinforcement Learning (RL) for adaptive bandwidth allocation, the system ensures optimal utilization of available resources while maintaining fairness and responsiveness to critical events.

The introduction of an Emergency-Aware Prioritization Module enables the network to reallocate resources dynamically during high-priority or life-critical situations, ensuring minimal latency and data loss for ultra-critical traffic such as health monitoring or industrial safety control. The accompanying Flask-based real-time dashboard provides intuitive visualization of key performance metrics—such as bandwidth utilization, fairness index, and traffic classification—allowing network administrators to monitor and manage the system efficiently.

Simulation results validate the system's capability to maintain near-optimal bandwidth utilization (≈100%), ensure fair resource distribution (Jain's Index ≈ 0.9), and deliver fast emergency response adaptation under varying load conditions. These findings affirm that the proposed model significantly enhances network intelligence, adaptability, and reliability compared to static or rule-based approaches.

Although the current implementation primarily relies on simulated IIoT traffic, future work will focus on integrating real sensor data and deploying the model in a testbed 5G/6G environment for field validation. Further improvements may include multi-agent reinforcement learning for distributed control, edge computing integration to reduce latency, and predictive analytics for proactive network management.

In conclusion, the system marks a significant step toward realizing autonomous, AI-driven, and emergency-resilient IIoT communication systems, capable of supporting the stringent performance demands of next-generation industrial and mission-critical networks.

REFERENCES

[1] F. Tang, L. Zhang, X. Zhou, and J. Wu, "Intelligent Resource Allocation for Industrial IoT in 5G/6G Networks: A Deep Reinforcement Learning Approach," IEEE Transactions on Industrial Informatics, vol. 18, no. 7, pp. 4872–4884, Jul. 2022.

[2] J. Wang, C. Jiang, K. Zhang, Y. Ren, and L. Hanzo, "Network Slicing Assisted Resource Management for Service-Oriented Ultra-Dense 6G Networks," IEEE Journal on Selected Areas in Communications, vol. 38, no. 2, pp. 294–306, Feb. 2020.

[3] K. Sood, S. Yu, and Y. Xiang, "Software Defined Wireless Networking Opportunities and Challenges for Internet of Things: A Review," IEEE Internet of Things Journal, vol. 3, no. 4, pp. 453–463, Aug. 2016.

[4] X. Chen, Z. Zhao, C. Wu, M. Bennis, and H. Zhang, "Reinforcement Learning for Resource Allocation in 5G Ultra-Dense Networks," IEEE Network, vol. 33, no. 4, pp. 52–59, Jul.–Aug. 2019.

[5] S. Dey, "Machine Learning Based Traffic Prediction and Dynamic Resource Allocation in 5G Networks," IEEE Access, vol. 8, pp. 132802–132815, 2020.

[6] [6] H. Zhou, T. Han, and N. Ansari, "Learning-Based Bandwidth Allocation in Heterogeneous IoT Networks," IEEE Internet of Things Journal, vol. 7, no. 9, pp. 8902–8912, Sept. 2020.

[7] M. Chen, Z. Yang, W. Saad, C. Yin, and M. Shikh-Bahaei, "A Machine Learning Framework for Resource Allocation in 5G/6G Networks," IEEE Transactions on Wireless Communications, vol. 20, no. 7, pp. 4310–4323, Jul. 2021.

[8] Flask Documentation, "Flask Web Framework," [Online]. Available: https://flask.palletsprojects.com/

[9] TensorFlow Documentation, "Building LSTM Networks for Time-Series Forecasting," [Online]. Available: https://www.tensorflow.org/

[10] OpenAI, "Reinforcement Learning: Policy Gradient Methods," [Online]. Available: https://spinningup.openai.com/en/latest/

[11] S. Kumar, P. Singh, and R. Tripathi, "Emergency-Aware Prioritization for Critical IoT Systems Using Reinforcement Learning," IEEE Access, vol. 10, pp. 112873–112885, 2022.

[12] A. Aijaz, "Towards 6G-Enabled Industrial Internet of Things: Key Performance Indicators, Use Cases, and Research Challenges," IEEE Internet of Things Magazine, vol. 3, no. 4, pp. 4–9, Dec. 2020.

[13] 3GPP TS 23.501, "System Architecture for the 5G System (5GS)," Release 17, 3rd Generation Partnership Project (3GPP), 2022.

[14] Y. Chen, T. Quek, and M. Peng, "Learning-Based Resource Management for Industrial IoT in 6G: Challenges and Opportunities," IEEE Communications Magazine, vol. 60, no. 2, pp. 44–50, Feb. 2022
.

[15] Gunicorn, "Python WSGI HTTP Server for UNIX," [Online]. Available: https://gunicorn.org