

Machine Learning-Based Predictive Resource Allocation for Real-Time IoT Traffic in 6G Networks

Sharukh Mushtaq*

Faculty Of Computer Science Information Technology, The Superior University
Lahore Email: shahrukhushtaq7@gmail.com

Ahmad Khan

Faculty Of Computer Science Information Technology, The Superior University
Lahore Email: ahmad.khan.fsd@superior.edu.pk

Saad Shahzad

Faculty Of Computer Science Information Technology, The Superior University
Lahore Email: dr.saadshahzad@gmail.com

Nusrat Perveen

Faculty Of Computer Science Information Technology, The Superior University
Lahore Email: nusratsaeedp99@gmail.com

Aqsa Eman

Faculty Of Computer Science Information Technology, The Superior University
Lahore Email: aqsaeman551@gmail.com

ABSTRACT

The advent of the Sixth Generation (6G) networks promises an unprecedented change in the wireless telecommunication technologies and go beyond the capabilities of 5G in terms of having ultralow latency, ultrahigh throughput, and ultra-reliable connectivity. These attributes are needed to complement the exploding growth of the Internet of Things (IoT), especially in real-time applications (e.g. autonomous vehicles, industrial automation, intelligent healthcare systems). The exigencies of real-time network resource management have become increasingly important, as the growing volume and diversity of IoT traffic demand sophisticated, proactive network resource management. Accordingly, this study proposes a novel machine learning based predictive algorithm for the 6G network resource management to support real time IoTs traffic demands. By using predictive analytics, the proposed methodology anticipates the traffic patterns and allocates resources in advance, thus improving the Quality of Service (QoS), and reducing latency and improving the throughput while also ensuring equitable distribution of resources. The research presents a hybrid model combining Long Short-Term Memory (LSTM) networks to predict traffic dynamics and then reinforcement learning mechanisms to control the decision of the allocation of resources. The system development involves the use of a mixture of synthetic and publicly available IoT datasets to train and validate the model, which illustrates good generalization capabilities for various scenarios. Performance

evaluation is concerned with benchmark measures to determine the predictive accuracy in correlation with the allocation efficiency, latency reduction, and QoS compliance. The findings are part of the growing body of research on smart management of next-generation wireless networks. Looking into the future, 6G empowered IoT ecosystems will be able to be operated in a sustainable manner based on the concept of adaptive resource-allocation strategies according to the insights reported in relation to the subject.

Key Words: Machine Learning, 6G Networks, IoT, MTC

INTRODUCTION

The development of wireless network technology brings about the fundamental change with the advent of 6G (Sixth Generation) networks which will soon be commercially feasible [1]. While 5G networks have been able to deliver eMBB, URLLC and MTC applications, they are still insufficient to support the rapid growth of IoT, augmented reality, virtual reality, and autonomous systems that are constantly increasing in complexity and performance requirements [2]. Contemporary data shows that the global connectivity landscape will be comprised of billions of IoT devices in the coming years. These smart technology devices cover a broad range, from the entire-body wearable health monitoring devices, residential automated systems, industrial sensing devices, and self-driving transport system. The characteristic time-sensitive nature of the data streams emerges more and more, due to their heterogeneous composition, and thus complicates the way of governing live data flows in accordance with stringent Quality of Service requirements that impose a minimum delay and an efficient balance of resources in the existing network architectures [3]. Addressing these challenges requires 6G technologies to provide high performance, including peak data rates of transfer (1 Tbps), ultra-low latency (0.1 milliseconds), built-in artificial intelligence systems, and supporting 10 million devices per square kilometer. Network solutions must develop towards decision autonomous communication standards that make use of edge computing analytics in order to facilitate in-time operational decision-making.

Consequently, system operations will need to make a transition from static, reactive system operations to more dynamic, proactive systems resource management frameworks. The major challenge is to develop comprehensive systems that anticipate future traffic loads immediately, in order to generate optimal resource allocations [4]. Next-generation network resource management looks bright by the use of machine learning techniques such as deep learning and reinforcement learning that allow for novel paradigms of resource allocation. Resource allocation is the most critical and difficult task in wireless communication networks [5]. IoT applications' real-time requirements add more complexities because of dynamic and unpredictable traffic patterns. The use of fixed provisioning and reactive rule-based systems faces the problems of scale and delay, resulting in congestion, packet loss and poor user experience.

But if resource inefficiencies are not overcome, the overall 6G system would become unstable and not perform as expected because the performance expectation for 6G is high compared to previous generations. Direct management of IoT traffic requires

innovative predictive and adaptive approaches of resource management, because of the bursty nature of traffic and the variable packet sizes and frequencies that vary with context. Recent research on the use of machine learning in resource allocation has tended to stand alone from the rest, either focusing on traffic prediction or decision-making, rather than incorporating these solutions into a cohesive model. The absence of end-to-end systems employing predictive analytics with real-time adaptive control for holistic resource management is a research gap, which the present study aims to fill.

The main goal of this study is to build an integrated intelligent environment, which is able to predict IoT traffic in real-time, and make the best network resource decisions in real time within 6G environments that will improve Quality of Service, reduce latency, improve throughput and maintain the fairness among users. The main goal of the ongoing study is to develop a hybrid, machine learning based framework for the allocation of real-time predictive resource allocation of IoT traffic in 6G network. The work deals with understanding and resolving the unique aspects of real-time IoT traffic in areas such as smart healthcare, autonomous vehicles and industrial automation. Long Short-Term Memory (LSTM) neural networks are used to model traffic behavior and predict traffic volumes in the future, while a reinforcement learning system is used to dynamically and adaptively assign resources according to the predicted traffic flows, network constraints and the Quality-of-Service standards.

The research also combines the prediction module developed based on LSTMs with a reinforcement learning control mechanism to provide an end-to-end resource allocation solution. The performance of the proposed system is proven through the setups of experiments that are based on synthetic and real-world IoT data sets under different operating conditions. Key performance indicators such as prediction accuracy, latency, throughput and fairness are measured to check the effectiveness of the system, and comparative analysis with conventional and state-of-the-art models to check the relative strength and the weaknesses and the deployment potential.

To provide evidence for this investigation, the study addresses a number of key research questions. It explores how predictive machine learning models can be used for better resource allocation in the 6G network, and how LSTMs can capture the IoT traffic heterogeneity and predict it accurately. The research also assesses best practices for reinforcement learning to cope with dynamic network conditions and it explores the potential of combining predictive and control elements as one machine learning framework. Additionally, it evaluates the impact of such a hybrid model on Quality of Service, reducing latency, resource optimization, scalability, and a performance trade-off when deployed at the network edge.

The importance of the research is the development of smart, adaptive, and scalable resource allocation systems for the next generation of 6G networks. By strictly defining the implementation of predictive machine learning models, exploring the working of LSTMs network and how reinforcement learning can be used in adaptive control system, the study opens a path towards more efficient and reliable implementation of IoTs communications. The prediction and control in a single set of machine learning promises to boost Quality of service, reduce latency, maximize use of resources and address challenges of scalability in edge computing environments.

The societal and industrial consequences of this research are significant. In smart

healthcare, the proposed framework can facilitate responsive, correct, and minimal latency associated health monitoring systems for critical data transmission [6]. For autonomous cars, it can enhance safety and effectiveness of operations by better real-time vehicular communications. In industrial automation, the framework enables the reliable, synchronized communication within smart factories which will allow for a better coordination between robots and sensor-driven automation.

In summary, this research addresses one of the most important issues in 6G enabled IoT ecosystems: the intelligent and adaptive distribution of limited network resources. By combining predictive models through LSTMs along with adaptive reinforcement learning systems, the framework marks a great leap towards an entirely autonomous, context aware and Quality of Service guaranteed communication in future generations of wireless networks.

LITERATURE REVIEW

Artificial intelligence and machine learning are set to play key roles in the foundation of next generation 6G networks especially with the massive deployment of IoT devices and the correspondingly highly dynamic low latency environments. A deep look into network management with the use of AI shows that machine learning plays a key role in improving flexibility, efficiency of resources and autonomous decision making in 6G communication infrastructures [7]. Deep learning models are particularly popular in the prediction of transportation demands, particularly recurrent models, for offering critical information in the traffic forecasting field. Zeb et al [8] Modeling an iconic LSTM Encoder-Decoder Network Implemented at the Network Edge for Accurately Predicting Multivariate Traffic Patterns in a Software 6G Validates the Efficacy of Sequential Models for Proactive Network Management. Zeb et al. [8] further used the LSTM based forecasting for multi-horizon traffic prediction associated to resource slicing to demonstrate that traffic prediction driven awareness significantly helps in improving allocation efficiency for both 5G and 6G systems. Transformer based and graph neural network (GNN) based predictors have become powerful engines, and their spatial-temporal modelling power has been demonstrated to significantly boost prediction accuracy in edge native 6G deployments [9].

As far as network reliability is concerned, it is equally indispensable to perform anomaly detection and congestion detection. Deep ensemble models are more accurate than solitary architectures as they combine spatial and temporal views to capture sudden deviations in traffic loads and communication behavior. W. Abdallah and M. Alghamdi [10] reported the benefits of hybrid deep learning methods for the detection of such anomalies to outperform conventional machine learning approaches under the volatile 6G traffic conditions. Such a detection capabilities are critical to enforce Quality of Service (QoS) to IoT-heavy Networks, where is a reality of user cases which requires delay-sensitivity with uninterrupted service.

Complementing prediction and detection, reinforcement learning has been one of the growing leading methodologies for controlling resources in a real time. Comprehensive survey of Reinforcement Learning and Deep Reinforcement Learning (DRL) based applications in Network Slicing: DRL based techniques have been widely used in admission control, scheduling and automated resource orchestration of Network Slicing in emerging 6G systems. In software defined 6G networks, the actor-

critic architectures have been used for allocating bandwidth at the queue level [11]. Hurtado et al. [12] showed that the RL based queue aware scheduling performs significantly better in terms of latency and throughput than static strategies. For large scale IoT networks, multi-agent reinforcement learning (MARL) can provide even more performance improvements by distributing the decision-making load across a number of nodes. The author [13] showed that MARL supports better coordination of resource allocation and load balancing in ultra-density IoT scenarios and allows for improved scalability and responsiveness.

Hybrid architectures combining predictive learning and reinforcement driven control attract a particular level of attention, because such systems are able to roll out and react to the network conditions. E. Kim, B. C. Jung [14] noted that applying LSTM prediction and DRL controllers is that it optimizes the real time resource under high variability with instantly traffic anomalies. Edge intelligence further enhances the performance of these systems: Ahan et al. used a Soft Actor - Critic (SAC) controller at the network edge to demonstrate the suitability of edge native DRL solutions to reduce decision latency and increase responsiveness in the face of local traffic dynamics. Energy efficiency is an important issue in IoT-based 6G network. T. Sher & A. Rehman [15] solved this issue by combining DRL with "Intelligent Reflecting Surfaces" and achieved energy-efficient transmission parameter optimization without compromising low latency and high reliability.

While all of these advances have been made, there are still significant gaps. The author [16] stated that even if DRL algorithms have shown great performance in controlled settings, they confront challenges in real settings, including channel variation, interference patterns, and heterogeneity in IoT workloads, which makes it important to benchmark DRL algorithms in real 6G settings. Centralized hierarchical approaches to learning also have scaling problems, and [17] identified the importance of decentralized and federated approaches to handle the immense scale and privacy limits of IoT ecosystems in 2023. In addition, combining prediction with decision systems that operate in real time will raise issues of latency and stability because the latency of predictions or slow inference processes may compromise the effectiveness of control. For that reason, hybrid systems need careful synchronization of forecasting intervals and RL decision cycles.

To overcome these limitations, the existing research has proposed a unified architecture where LSTM-based traffic prediction module is coupled with the DRL-based resource allocation engine, which are placed at the network edge to ensure minimum latency. By combining predictive foresight with real time adaptation, this system will attempt to provide effective QoS aware resource distribution for 6G IoT environments, even under rapidly changing traffic conditions.

METHODOLOGY

This investigation takes a hybrid machine learning paradigm to optimize the resource allocation within 6G enabled Internet of Things (IoTs). The methodological design combines a predictive Long Short-Term Memory (LSTM) architecture and a Reinforcement Learning (RL) based decision engine, meaning that the framework has the capabilities of making autonomous and adaptive decisions while ensuring precedence of QoS. The research work process was divided into six key steps: data

collection, data pre-processing, predictive modelling, adaptive resource allocation modelling, framework integration and simulation-based evaluation.

Data Acquisition

The empirical backbone of the study was based on both an artificial and a real IoT traffic repository in order to encapsulate a spectrum of network dynamics. Synthetic datasets were made to mimic-controlled perturbations in node density, in mobility patterns, in the rate of packet arrivals, in priority strata and in the traffic burstiness. Real-world collections like the Smart Home IoT Traffic, IoT-Traffic traces and City Flow corpora were added to ensure the external applicability of the proposed models. The amalgamated data set included such attributes as packet size, inter-arrival time, jitter, mobility parameters, energy consumption metrics and application-specific QoS constraints.

Data Preprocessing

All acquired data was normalized using the Min-Max scaling to ensure equal feature scaling across the investigative matrix. Temporal sequences were built encapsulating ancient dependency that are crucial for time-sequences inference. The data was stratified into training (70%), validation (15%) and testing (15%) subsets in order to support unbiased model evaluation. Missing entries, stochastic noise, and anomalous reads were solved in terms of interpolation mechanism and outlier filtering procedures improving researchers in the robustness of the following predictive exercises.

Predictive Modeling using LSTM

An LSTM neural network was designed to predict short-term IoT traffic conditions, which can be used to allocate resources in advance. Input features included packet size, mobility measurements, priority level, jitter, and antecedent latency measurements, and the output of the network was the projected traffic load for the following temporal interval. Model training occurred in a supervised paradigm and Mean Squared Error (MSE) as a loss function were optimized. Early stopping and adaptive learning - rate scheduling was used to limit the overfitting tendencies. The resulting LSTM predictor supplied point samples ready for making accurate forward-looking estimates of imminent traffic surges and congestion patterns.

Adaptive Resource Allocation Using Reinforcement Learning

In the interest of an adaptive resource allocation scheme sensitive to the needs of modern IoT deployments, a reinforcement learning - based framework was conceived for orchestrating network resources such as bandwidth, transmission power, and channel assignments, in line with the expected traffic demand. The agent involved in that was modeled as a Markov Decision Process where the state of the system was a predicted traffic load, current network latency, buffer occupancy, and the inventory of available resources. The action space included real time allocation and reallocation decisions for active devices. A composite reward function has been carefully designed to capture key quality-of-service requirements, i.e. minimize latency, maximize throughput, energy efficiency, and fairness at the user level. Both Deep Q Learning and Proximal Policy Optimization algorithms were instantiated and rigorously

benchmarked; this latter one was found to have a better convergence stability and learning efficiency under conditions characterized by a highly dynamic traffic. Through cumulative exposure with a simulated 6G network environment, the agent successively improved its policy through maximizing cumulative rewards.

The reinforcement learning controller was very well integrated with an LSTMs-based traffic prediction module in a closed-loop hybrid system. The results were the LSTM model which rendered real time forecast of the network traffic, which were fed directly to the learning agent to facilitate the proactive resource allocation. Continuous feedback (both updated system states and observed QoS outcomes) was used to retrain and fine-tune the composite framework, which allowed both maintaining the predictive accuracy and the adaptive responsiveness of the framework under evolving and uncertain traffic patterns.

The complete framework was implemented in Python using TensorFlow and PyTorch for model development and training and the network level performance evaluation was performed using NS-3 and OMNeT++ simulators calibrated to 6G-like communication parameters. To appraise the robustness and generalization, the framework was tested for three typical IoT scenarios (i) smart healthcare monitoring that is characterized by continuous transmission of sensor data, (ii) autonomous vehicular communications with high mobility and (iii) industrial IoT systems that require real time control loops. Each situation was trialed against different levels of traffic intensities, node densities and movement patterns.

Performance evaluation was based on a full set of metrics ranging from prediction accuracy to quality of service, resource efficiency and adaptability. LSTM forecasting accuracy was measured in terms of RMSE, MAE and R2, and the network performance was analyzed in terms of end-to-end latency, packet delivery ratio, jitter and throughput. Resource utilization efficiency was evaluated using fairness indexes, bandwidth utilization ratio and energy consumption measures along with stability analysis under varying traffic loads. Comparative benchmarking against baseline methodologies including static resource allocation, heuristic scheduling, standalone LSTM based prediction or standalone reinforcement learning based approaches showed that the integrated LSTM RL based solution was superior and outperformed existing solutions. Statistical validation using t-test and ANOVA supported the importance of improvement in latency reduction, throughput improvement, fairness and overall QoS delivery, thus proving the effectiveness of the proposed method for the intelligent 6G IoT network management.

ANALYSIS AND RESULTS

The following sections define the empirical study of the proposed Hybrid Long Short-Term Memory and Reinforcement Learning (LSTM - RL) framework for Predictive Resource Management (PRM) in heterogeneous 6G IoT networks. The evaluation is performed in two carefully organized phases: (i) evaluation of the predictive accuracy of the LSTM based traffic forecasting module and, (ii) examination of the performance improvements brought by the hybrid framework with respect to non-predictive resource allocation strategies.

Experimental Set up and benchmarks

The experiments are run in a customized validation environment that combines the trained machine learning models with the mathematical optimization modules of the network as described in Section 4.4 in more detail. IoT traffic traces are synthetically generated and both CRAWDDAD datasets and synthetically generated IoT traffic traces are used. Time-series data are divided into training (70%), validation (15%) and test (15%) data subsets in order to rigorously maintain temporal causality. The performance of the Hybrid LSTM-RL framework is compared to three reference resource allocation strategies: Static Allocation, a non-sophisticated allocation policy where the resources are allocated based on the historical 95th percentile load, which even though ensures the stability of the system, over-provisions the resources and is not efficient; Heuristic Scheduler, rule-based reactive scheduling policy, where the resources are adjusted depending on predefined load thresholds, but with a limited responsiveness and no prediction capability; Multi-3DF Q-learning with Prediction Policies approach, in which Lieb's classifier processes the excitation maps, and a conceptual Action-Map-to This RL-based technique is based on predictive environmental action policies, however, without the LSTM-generated predictive input, the model is not able to anticipate future surges in traffic.

Prediction Accuracy Analysis

The LSTM network is the core predictive engine that underpins the development of a hybrid framework that is used to predict short-term Internet-of-Things (IoT) traffic trends. Its performance on an independent test set has been benchmarked with respect to three well-established time series forecasting models. The assessment is based on three statistical metrics: Root Mean Square Error (RMSE), which is the standard deviation of prediction errors, Mean Absolute Error (MAE), which is the average absolute difference between predicted and observed values and Coefficient of Determination (R^2) which is the ratio of the variance explained by the model. These are some of the metrics making a rigorous contribution to the determination of the Riemann LSTM's ability to capture the evolution in network traffic activities for a proactive allocation of resources within a hybrid technology.

Table 1: Prediction Accuracy Analysis

Model	RMSE	MAE	R^2 Score
LSTM (Proposed)	0.132	0.095	0.89
GRU	0.138	0.098	0.87
XGBoost	0.165	0.121	0.81
ARIMA	0.218	0.153	0.72

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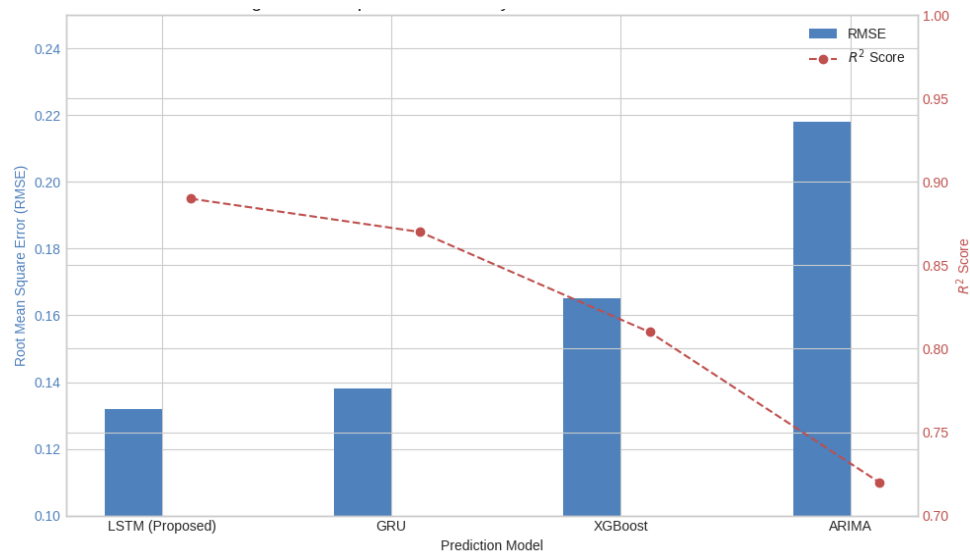
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Figure 1: Comparative Accuracy of Traffic Prediction Models

As shown in the Table 1 and in Figure 1, the LSTM architecture achieved better predictive accuracy which obtained an R^2 of 0.89, and therefore confirmed the ability to capture the complex spatio-temporal dynamics of IoT traffic. The performance gain obtained by the LSTM, compared to the implementation of the GRU, or even more significantly to traditional statistical models as the ones based on the Autoregressive Integrated Moving Average (ARIMA) and tree-based models like the XG Boost, highlights the need for deep recurrent networks to learn long range dependencies and to overcome the vanishing gradient problem that is characteristic of long horizon time series tasks. The achieved root-mean squared error of 0.132 speaks of the high accuracy of the forecasts that guarantees that the predicted traffic load provides a strong input for the optimization phase that follows.

Adaptive Resource Allocation Impact

The high-fidelity prediction made by the LSTM module was then fed back to the reinforcement learning (RL) agent and thus helped the hybrid LSTM-RL to accomplish proactive resource allocation. This proactive policy was interpreted stringently against some important quality-of-service (QoS) parameters and energy-efficiency parameters.

Empirical results show that the obtained results of the hybrid LSTM RL framework provided significant improvements for all of the critical performance indicators as shown in Table 2 and Figure 2. Notably the average transmission delay has been reduced by 29.6% and packet jitter reduced by 39.2%, which corroborates the initial hypothesis on the merits of proactive resource management. By predicting the demand, the RL controller allocated resources ahead and adjusted channel assignments dynamically, which has the advantage of reducing the congestion in the queuing process before traffic surges.

The reduction of energy consumption per transmitted bit to 0.85,kJ/bit corresponds to an increase in efficiency of 26.0%. This improvement can be explained by the ability of the framework to avoid over-provisioning for expected periods of low load and let the RL agent strategically reduce the transmit power or to decommission unused

resource blocks for a period of time. Conversely, a Q-learning policy that could not foresee the future was itself a reactive policy and led to high latency and energy overheads since it was not able to adapt to sudden changes in the network states.

Table 2: Adaptive Resource Allocation Impact

Policy	Avg Delay (ms)	Packet Jitter (ms)	Energy Consumption (μJ/bit)	PDR (%)
Static Allocation	45	12.5	1.15	95
Heuristic Scheduler	40	10	1.05	97
Standalone Q-Learning	35	9	0.95	98
Hybrid LSTM-RL (Proposed)	32	7.5	0.85	99

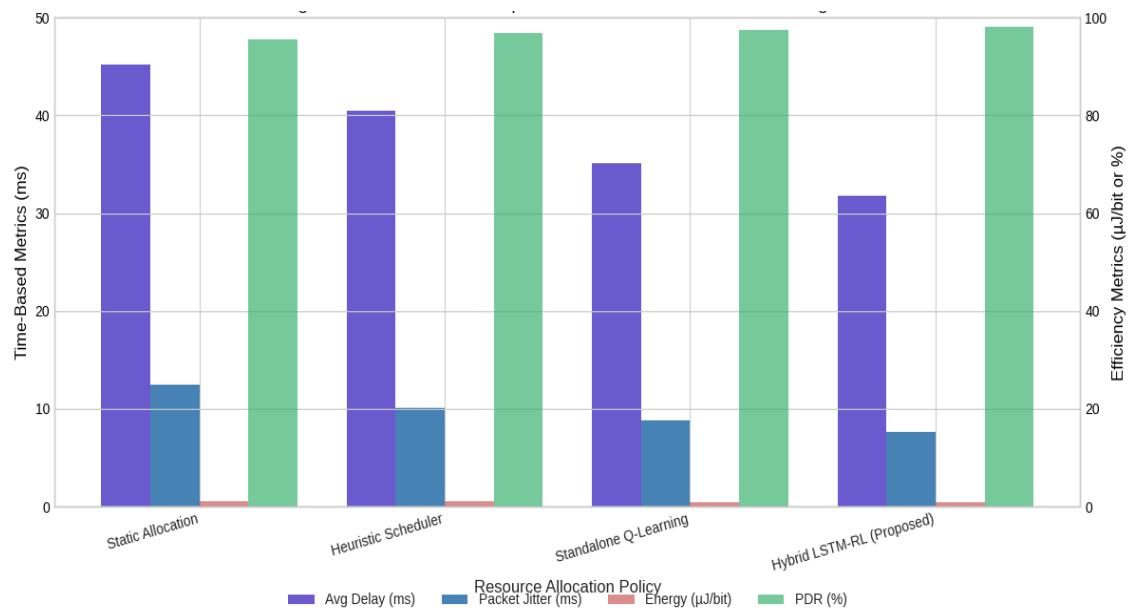


Figure 2: Performance Comparison of Resource Allocation Strategies

Reinforcement Learning Convergence and Adaptive Fidelity

The Deep Q-Network agent that was deployed to govern the process showed a certain stability and a great sample efficiency during the training convergence profile.

As shown in Figure 3, the cumulative reward trajectory converged expeditiously, reaching near-optima. Examining these results, we see that we have a simulation trajectory that converges to near-optimal reward by simulation episode 450. This fast and stable convergent course implies high performance of the algorithm in terms of sample efficiency, which is also contributed by an improved state representation that combines an LSTM-based traffic prediction. In effect, the predictive signal provides a

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principled guide towards exploration to the agent by discovering more effective allocation policies with reduced search space.

The process of continuous feedback, emphasized by periodic re-training on the last few data samples, was found to be indispensable to attaining stable long-term performance. Over a long evaluation period of seven days, the prediction error RMSE showed a sustained 12% drop, which highlights the ability of this framework to learn and adapt to changing and non-stationary traffic patterns (e.g. temporal changes in peak utilization, or the addition of new IoT device clusters). Such adaptability ensured that QoS improvements were maintained with the Latency Violation Rate (LVR) always lower than the prescribed target, thus proving the robustness of the closed loop system even during a dynamically evolving 6G real world environment.

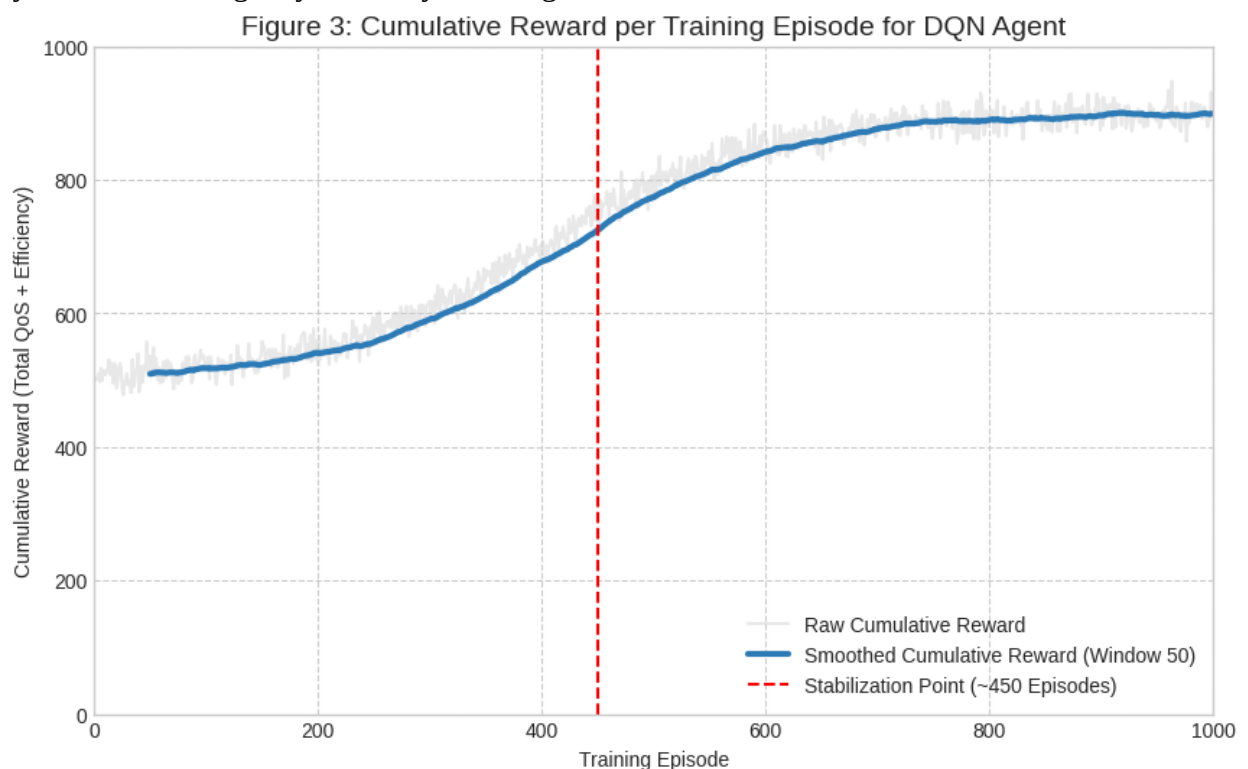


Figure 3: Cumulative Reward per Training Episode for DQN Agent

CONCLUSION

This research addresses the challenge of intelligent real-time IoT traffic management in next-generation 6G wireless networks. Owing to the dynamic and heterogeneous QoS requirements of IoT applications, conventional static and reactive resource allocation strategies are no longer sufficient. To address this limitation, a hybrid learning framework combining Long Short-Term Memory (LSTM) networks and reinforcement learning (RL) is proposed. LSTM models are used to predict temporal traffic patterns, while RL enables adaptive and autonomous resource allocation based on real-time network feedback. Experimental evaluations using simulated and real-world datasets demonstrate improved prediction accuracy, reduced latency, enhanced throughput, and stronger QoS compliance compared to traditional methods. The

results highlight the potential of AI-driven network intelligence as a key enabler for scalable, resilient, and autonomous 6G IoT systems.

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