JOURNAL OF EMERGING TECHNOLOGY AND DIGITAL TRANSFORMATION

ONLINE ISSN
3006-9726

PRINT ISSN
3006-9718

VOLUME 5 ISSUE 01 (2026)

Spatio-Temporal Traffic Prediction and Proactive Resource Management for Scalable LoRaWAN Networks

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Abstract:

Large scale Internet of Things (IoT) deployments such as Low Power Wide Area Networks (LPWANs) and the LoRaWAN have become central to the large-scale Internet of Things (IoT) deployment because of their long-range communications and low energy use. Nevertheless, the scalability and reliability of LoRaWAN networks is inherently limited by the unslotted ALOHA-based medium access scheme, fixed resource setup and severe regulatory constraints of duty-cycle. The difficulties are magnified in crowded and mobile setups like smart cities, where non-stationary and heavy traffic conditions result in severe packet collisions, high latency and poor quality of service (QoS). In this paper, a smart, predictive, and duty-cycle-aware resource management framework is proposed to be utilized by LoRaWAN networks that would reorganize network operation by transitioning it to reactive control to proactive decision-making. The proposed solution combines a hybrid Spatio-temporal traffic prediction model with Graph Convolutional Networks (GCN) and Gated Recurrent Units (GRU) as well as an adaptive resource management module that is placed at the edge of the network. Through learning of spatial contours between the entities in the network and time-based traffic dynamics, the framework effectively predicts short time congestion and pre-emptively modulates spreading factors, channels, and transmission scheduling and maintains the entire regulatory adherence. Extensive tests based on actual traffic traces and high-density simulation evidence that the suggested framework is far superior to the traditional LoRaWAN Adaptive Data Rate (ADR) schemes and the established machine learning model. GNCN-GRU model provides a 18% decrease in the error of traffic prediction relative to the conventional recurrent models with the resource adaptation being proactive which minimizes the packet collisions by up to 30 percent in the ultra-dense situation. Besides, the framework maintains up to 21% increase in the ratio of packet delivery at the 1000 nodes per gateway, and it ensures a sub-500ms latency of mission-critical traffic despite a rigid duty-cycle limit. The experiments of edge deployment prove the viability of the method, with a latency of inference of less than 42ms and a minimum of computational cost. Comprehensively, the findings indicate that edge Spatio-temporal intelligence is feasible and applicable to scalable, reliable, and regulation-friendly LoRaWAN operation, and the next-generation smart city and industrial IoT applications are feasible.

Key Words: *LoRaWAN; IoT Traffic Prediction; Spatio-Temporal Deep Learning; Edge Intelligence; Adaptive Resource Management; Duty-Cycle Aware Scheduling.*

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

1. Introduction

The Internet of Things (IoT) has fundamentally redefined how devices can communicate, interact, and coordinate the exchange of information and data, thus, making it possible to achieve pervasive sensing and autonomous functioning across a wide-range application scope, including smart cities, environmental monitoring, precision agriculture, medical systems, and automation within an industrial environment (Bonilla et al., 2023; Farhad and Pyun, 2023). This has been triggered by the realization of communication technologies which are able to facilitate the huge number of devices connected to the Internet of Things even as they remain ultra-low in power usage, long in communication range as well as minimal infrastructural cost. In this regard, Low Power Wide Area Networks (LPWANs) have appeared as a foundation of the large-scale IoT connectivity, as they provide long-range wireless connectivity at very low energy consumption, thus allowing battery-powered devices to operate years continuously without maintenance interventions.

LoRaWAN (Long Range Wide Area Network) is one of the LPWAN technologies that have received a large amount of scholarly publication due to the open standard design, flexible deployment architecture, and alignment with a wide range of IoT applications (Bonilla et al., 2023; Farhad and Pyun, 2023). LoRaWAN uses a star-of-stars topology whereby lightweight end devices send uplink packets straight to one or multiple gateways, which, in its turn, routes the information to a central network server where it is then processed and controlled. The said architectural paradigm enables scalable connection over a number of kilometres without consuming much power at the device level. Therefore, LoRaWAN has found wide use in the smart metering, environmental sensing, waste management, industrial IoT, and urban mobility systems both in metropolitan and rural settings (Bonilla et al., 2023).

Although LoRaWAN has its advantages, it also has inherent challenges that limit its scalability and throughput in addition to Quality of Service (QoS) especially in densely deployed applications. LoRaWAN employs the unslotted pure ALOHA access scheme at Medium Access Control (MAC) layer enabling end devices to send and transmit without any previous channel measurements. This mechanism is intuitively straightforward and energy efficient, but significantly adds the risk of packet collisions with the increase of the density of the devices and the volume of traffic (Povalac et al., 2023; Bonilla et al., 2023). Also, regulatory duty-cycle restrictions place strict conditions on channel access forcing the devices to delay transmissions following the delivery of packets. These constraints exacerbate the latency, constrain the effective throughput and further congestion at bursts in the traffic. These consequences are sharply felt in smart cities in which heterogeneous devices generate intermittent event-based traffic, which form highly dynamic and unpredictable network behavior (Povalac et al., 2023).

Among the most obvious disadvantages of the current implementations of the LoRaWAN lies the fact that they are ad-hoc and fixed in configuring parameters of networks configuration such as the spreading factor (SF), the transmission power and the channel allocation. They are generally configured in a standard manner or in a reactive manner without consideration of altering the traffic dynamics or the existing network properties (Bonilla et al., 2023). This contributes to the reality that the LoRaWAN networks tend to lack an effective spectrum allocation, retransmission, increased packet loss and diminished quality of service. It has been discovered that they particularly pose a threat to latency-and mission-critical IoT applications

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

i.e., real-time monitoring, emergency response systems, and smarter transportation networks.

To address these impediments, machine learning (ML) has become a potential technology to facilitate intelligent, predictive, and adaptive management of the networks within the IoT. Knowing the historical and the current tendencies of the networks, the ML models will be able to forecast the future of the traffic and assist in planning the resources proactively (Farhad and Pyun, 2023; Alkhayyal and Mostafa, 2025). In particular, sequence-learning based models, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) neural networks, have been demonstrated to be extremely efficient in non-linear time-series modelling of time-dependencies as well as taking into account long-term time-dependencies. These features make them particularly appropriate in traffic prediction tasks in the wireless communication networks, where the traffic dynamics are frequently complex and non-stationary (Alkhayyal and Mostafa, 2025). Deep learning models have a better ability to model bursty traffic patterns and temporal correlations that conventional statistical methods like ARIMA or SARIMA cannot model, arising in real-life applications of IoT deployments.

More recent developments on edge intelligence also increase the feasibility of ML-based optimization of LoRaWAN networks. The predictive models can now be done in a lightweight manner and therefore can be deployed directly to a gateway or local edge server; thus, the near real-time inference can be realized with a smaller latency, forcing less backhaul as well as added energy efficiency. Using such a combination of traffic forecasts and adaptive control, including the duty-cycle-conscious scheduling, the dynamically allocated spreading factor, and reconfigured channels, LoRaWAN networks will be able to significantly mitigate packet collisions, improve the ratio of packet deliveries, and high throughput when the network is subject to variable conditions (Farhad & Pyun, 2023; Alkhayyal and Mostafa, 2025). As an example, boosting-based ML has proven to be very fruitful in enhancing path loss prediction and network performance under a variety of environmental factors, thus highlighting the potential practical utility of advanced ML-driven optimization (Alkhayyal and Mostafa, 2025).

Despite the fact that previous research has focused on the implementation of ML solutions to single LoRaWAN optimization issues (e.g. energy efficiency optimization, spreading factor optimization, and anomaly detection), most of the existing solutions to these problems consider each of them individually. A literature review of LoRaWAN and artificial intelligence integration demonstrates that there is an increasingly growing interest in the research area but indicates that there is a lack of end-to-end models that combine both traffic prediction and proactive resource management with deployment limitations (Bonilla et al., 2023; Farhad and Pyun, 2023). Specifically, the intelligent traffic forecasting and its direct integration with adaptive network control within the circumstances of duty-cycle constraints is not a well-researched area.

Driven by these gaps, this study suggests an intelligent traffic prediction framework by machine learning in IoT networks based on LoRaWAN. This approach is a combination of the latest time-series deep learning models and the use of Spatio-temporal feature extraction to precisely predict the short-term and medium-term traffic flow. They are then operationalized into adaptive resource management policies that implemental the network parameter to avoid network congestion, decreased latency, and improved network stability. It lays more stress on a practical life implementation considering the applicability of the edges deployed to actual deployment and the allocated computational resources and the suitable handoff with the already deployed LoRaWAN protocol stacks.

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

The main contributions of the work include the holistic study of LoRaWAN traffic behavior with the help of both real-world and synthetic data to determine the salient Spatio-temporal factors affecting congestion and performance degradation; the creation and testing of ML-based predictive models that greatly surpass the traditional statistical baselines; and the demonstration of proactive and prediction-based resource management strategies that can produce a quantifiable improvement in the reduction of collisions, packet delivery, and QoS. All together, these contributions improve the state of the art in the intelligent management of LPWANs and help to create the scalable, energy-efficient as well as self-optimizing infrastructures of smart IoT communication.

2. Literature Review

The current rapid growth of the Internet of Things (IoT) has required the necessity to make a radical shift in the approach to managing the network, and replace the rule-based and static structure with adaptive, intelligent, and self-organizing communication structures. Since deployments of IoT grow in size and heterogeneity, conventional network control tools can no longer be reliably, efficiently, or provide Quality of Service (QoS). Thus, the current literature has been concerned with identifying the drawbacks of already available Low Power Wide Area Network (LPWAN) technologies, specifically LoRaWAN, and investigating the possibilities of machine learning-inspired approaches to forecasting traffic, optimization of resources, and control of the network in real-time. The current literature falls into four research areas that are closely related to each other, namely scalability and MAC-layer limitations in LoRaWAN, use of deep learning to predict traffic, ML-based resource optimization strategies, and the new paradigm of edge intelligence.

The basic issue with LoRaWAN networks is the architecture of its Medium Access Control (MAC) layer based on unslotted Pure ALOHA access scheme. Although this technique reduces the complexity of the devices used and their power use, it greatly affects scalability. The likelihood of packet collisions rises at a high rate with the degree of device density with a resultant sharp decline in Packet Delivery Ratio (PDR). Povalac et al. (2023) work with demonstrating that, by dense deployments, the probability of collision grows non-linearly, and the capture effect, which makes the stronger communications mutable weaker messages concurrently, only enhance unfairness and packet loss even further. Such effects are amplified especially in urban IoT cases where heterogeneous devices cause asynchronous and bursty traffic.

The assumption of perfect orthogonality is not true in LoRaWAN though the spreading factors (SFs) are quasi-orthogonal used to reduce interference; this does not occur when the traffic load is high. Bonilla et al. (2023) disclose that inter-SF interference is severe when there is an occupancy in channels, compromising the efficacy of SF diversity, and leads to a greater amount of packet corruption. Besides interference issues, regulatory duty-cycle constraints provide rigid constraints concerning the use of the channels. In band like the EU868 band, 100 percentage restriction on duty-cycle is a severe constraint to transmission opportunities. As demonstrated by Farhad and Pyun (2023), the duty-cycle cool-down times in traffic bursts are not considered by the static Adaptive Data Rate (ADR) mechanisms, which result in the overflow of the buffers, the excessive delays in the queue, and the high latency rates. All these constraints underscore the inefficiency of the traditional, reactive configuration approaches in the dynamic IoT settings.

In order to mitigate the random nature of the ALOHA-based access, recent works have considered the concept of time-series traffic forecasting as a way of predicting congestion and proactively controlling the network. The conventional statistical models, e.g. ARIMA, are becoming inappropriate to IoT traffic

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

because it is based on assumptions of linearity and stationarity. On the contrary, deep learning models have performed better to model non-linear and non-stationary dynamics in traffic. Alkhayyal and Mostafa (2025) offer an extensive comparison of the Recurrent Neural Network (RNN) architectures presenting that both Long Short-term Memory (LSTM) and Gated Recurrent Unit (GRU) are more effective than classical approaches in their ability to capture long-term temporal dependencies. The LSTM networks are especially efficient to detect the periodic traffic patterns typical of smart metering and environmental sensing whereas GRU ones provide a similar level of accuracy with a lower level of computational complexity, making them appealing to latency-sensitive tasks.

In addition to the purely temporal modelling, the recent literature focuses on the significance of describing spatial correlations between IoT devices. Computation Traffic patterns in LoRaWAN Network are not only time dependent but also space dependent due to clustering of devices, distribution of load on the gateway, and propagation environment. The authors present hybrid Spatio-temporal architectures that represent LoRaWAN deployments as graphs and apply Graph Convolutional Networks (GCNs) to extract spatial features after which they are fed into the LSTM networks, which later predict the temporal features (Dai et al., 2025). These methods prove to be more accurate in forecasting especially in thick networks where the issue of spatial congestion is eminent.

Machine learning has been used to build upon predictive capabilities, and has previously been used to allow proactive resource optimization in LoRaWAN networks. Instead of depending on the heuristically-based ADR schemes, ML-based approaches strive to adjust the parameters of a network dynamically, depending on the forecasted conditions. Nisar et al. (2025) suggest an ML-based framework of adaptive spreading factor and transmission power assignment that makes use of the predicted Signal-to-Noise Ratio (SNR) trends. Their findings reveal that their results demonstrate an energy saving of up to 25 percent over the standard LoRaWAN setup, and at the same time the reliability is also increased. In cases when the training data is sparse, ensemble and boosting methods have been of interest. According to Farhad and Pyun (2023), by increasing algorithms like XGBoost and Light_GBM, the accuracy in link-quality and path-loss prediction are high, which makes them a successful trade-off between the efficiency of a given algorithm and the predictability in environmental monitoring application.

The increasing interest in edge computing has contributed to the practicality of intelligent LoRaWAN optimization even more. Cloud-based management is centrally located, which causes latency and backhaul overheads that do not suit IoT services that need timeliness. Edge intelligence is a solution to such issues because it allows inference and control to be brought nearer to the data source. Alkhayyal (2025) examines the idea of lightweight MLs installed on LoRaWAN gateways, showing significant trade-offs to be parameter pruning and quantization of model, which avoidional waste computational and memory consumption and predict accurately. Gateway level inference leads to the near real time reconfiguration of network configurations as it minimizes response time to mission critical applications like emergencies alerts and industrial surveillance.

There is a new body of research which is applying traffic prediction in conjunction with enhanced scheduling logic taking duty-cycle constraints into explicit consideration. Instead of responding to collisions once they have occurred, gateways have the opportunity to use anticipated levels of congestion to pre-compute transmission windows and actively command end devices to switch channels or spreading factors. Even though there is some early

ONLINE ISSN
3006-9726

PRINT ISSN
3006-9718

VOLUME 5 ISSUE 01 (2026)

evidence of the possible effectiveness of such predictive scheduling, this field has not been investigated extensively, especially in real-world implementation practice where both regulatory limitations and traffic variability exist.

Even though there has been a considerable improvement in these areas, a gap in research is still present. The other literature tends to treat the issues of predicting traffic and optimizing resources separately, leading to disjointed solutions which do not reflect the inter-relationships between predictive quality, regulatory complexity and operational viability. In addition, most of the suggested ML methods are also tested on synthetic data, which is not entirely representative of bursty, irregular and context-dependent real urban IoT traffic. Avoidable gaps exist in end to end, edge deployable, frameworks, which combine Spatio-temporal traffic prediction and proactive, duty-cycle, conscious resource management in realistic operating scenarios. This gap is necessary in order to achieve scalable, reliable, and intelligent LoRaWAN networks that can be used to support next-generation IoT applications.

Table 1: Comparative Analysis of LoRaWAN Resource Management Approaches

Feature	Statistical Models (ARIMA)	Standard ADR	ML-Based Proactive ADR	Proposed Framework
Traffic Handling	Linear only	Reactive	Non-linear/Predictive	**Spatio-Temporal/Adaptive**
Latency	High	Medium	Low	**Ultra-Low (Edge-based)**
Scalability	Low	Low	Moderate	**High (Intelligent)**
Duty-Cycle Aware	No	Yes (Static)	Often Neglected	**Yes (Direct Integration)**

3. Methodology

The research provides a predictive and adaptive traffic-aware resource management in the LoRaWAN networks. The methodology has been designed in such a way that it integrates traffic forecasting, based on machine learning, into the realities of deployment, such as regulatory duty-cycle constraints, computational cost and usability in real time. The suggested solution is based on a systematic pipeline that includes the data collection, Spatio-temporal features modelling, predictive inference at the network end and proactive resource adaptation.

System Architecture

The recommended framework uses a distributed model based on the intelligence architecture which decouples model training and inference to guarantee scalability and deployment. Offline model training and hyperparameter optimization are done off the centralized server and based on historical traffic traces. This is a stage that allows a large-scale exploration of model configurations without exerting a high computational constraint on the network infrastructure. After the training, the prediction model is reduced in size and implemented on the level at the LoRaWAN gateway. This is carried out by inference at the gateway that can to estimate traffic near real time and control decisions on the network without depending on cloud-based processing. This edge-based design minimizes the control-loop latency and backhaul traffic and allows gateways to operate as smart controllers which can react immediately to the changing network conditions.

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

Data Mining and Characterizing Data

A hybrid data strategy is used to guarantee the ability to generalize to a variety of operational conditions. Traffic traces of the urban-scale LoRaWAN system reported by Povalac et al. (2023) are obtained in the forms of real-world traces, and they include realistic propagation scenario, interpreter interaction and heterogeneity of the traffic. In order to supplement such data, artificial traffic is created with the help of the NS -3 LoRaWAN simulation module, which permits to evaluate it controlled in the framework of high-density deployment and burst traffic events. Raw metadata on packets and protocol headers are translated into structural representations of features. Temporal characteristics consist of inter-arrives times of packets, moving averages of traffic and periodically recorded indicators of diurnal and weekly cycles. The Signal-to-Noise Ratio (SNR), Received Signal Strength Indicator (RSSI), frequency error is also included in the feature of link-quality in order to describe the channel conditions. Moreover, the network-level indicators, i.e., spreading factor occupancy and sub-band duty-cycle usage are derived so that the situational awareness of network load and the regulatory constraints can be achieved. This multi dimension feature space allows the predictive model to acquire elaborate interactions among the dynamics of traffic and resource availability.

Spatio-temporal Traffic Forecasting Model.

The LoRaWAN traffic dynamics depend on both the dynamics of time and spatial correlations that are caused by the overlapping of gateway coverage and node dispersion. The proposed predictive engine uses a hybrid Spatio-temporal learning architecture in order to capture these dependencies. A Graph Convolutional Network (GCN) is used to model spatial relationships with network entities being modelled as nodes and scenes being connected with each other and shared channels through a graph edge. The GCN acquires the spatial congestion patterns and propagation of interface between neighbouring gateways which reduces hidden-node effects as well as localized overload situations. A Gated Recurrent Unit (GRU) Network then takes the features that were spatially encoded and attempts to capture any temporal dependency. GRU architecture is chosen because the architecture has a good balance between expressive power and computation efficiency. It can store long-term dependencies, like traffic cycles, at a lower number of parameters than Long Short-term Memory (LSTM) networks can store. This design will provide the ability to correctly make predictions and at the same time be capable of running on hardware with limited resources of a gateway.

Pre-emptive Reactive Resource Management

The Spatio-temporal model provides traffic forecasts which are transformed into proactive network responses in an Adaptive Resource Management (ARM) module. The ARM module is predict-then-act based, which allows performing preventive mitigation of the congestion before packet collisions and undesired delays. As the model predicts the spread load of the particular spreading factors or channels, the ARM module will compute different settings and provide downlink MAC commands to dis-assign, and reassign feasible devices, to less crowded resources. This is proactive reconfiguration that redistribution of traffic load and minimizing the probability of collision. Precise message tier limiting regulatory constraints are formally reflected in the logic of adaptation. A credit-based system of tracking the use of the duty-cycle is used to continually track the sub-band usage in accordance to regional rules, e.g. the 1 percent duty-cycle limit within the EU868 band. In case the predicted demand is greater than the allowable transmission capacity, the scheduler uses a priority-conscious deferral mechanism. The priorities are given to time-sensitive traffic and the non-essential periodical transmissions

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

are postponed to ensure compliance and quality of services.

Implementation and Edge Deployment Python Java Perl .NET Java Lovelace

The framework suggested is executed with the help of PyTorch to develop the model and train it. To deploy a trained model, trained models are converted to lightweight inference formats with the TensorFlow Lite microcontrollers. The target deployment devices are gateway-like platforms, which are Raspberry-based gateways and gateways based on industrial LoRaWAN foundations that have an embedded accelerator. Parameters pruning and quantization are used as model optimization tools to make sure that inference latency is lower than standard LoRaWAN packet inter-arrival times. This ensures that predictions and related network modifications can be pursued in near real time without the need to interfere with the regular operations of the gateway.

Evaluation Metrics

The work of the proposed methodology is measured with the help of both predictive and network-based measurements. The standard time-series error measures are used to measure the accuracy of prediction. The parameters used to measure the network performance are Packet Delivery Ratio (PDR), collision probability, throughput, and end-to-end latency. The analysis of energy efficiency is also done to make sure that extra signaling of control does not contribute a lot of extra power at end devices. Combined, these measures give a holistic evaluation of the framework in enhancing the scalability, reliability and efficiency of operation of Lora WAN.

4. Results and Discussion

Traffic Prediction Accuracy Analysis

The comparison of the accuracy of four models, namely ARIMA, LSTM, Standard RNN and the proposed GCN-GRU framework, in predicting traffic in terms of the Mean Absolute Error (MAE) is shown in figure 1. Reducing values of MAE denote enhanced prediction performance. The original ARIMA model demonstrates the largest MAE ([?]0.14), which indicates its weakness in the ability to model the very dynamic and non-stationary traffic patterns that are a characteristic of the LoRaWAN-based IoT networks. Although ARIMA is useful in linear and stationary time series, it does not achieve the characteristic of abrupt changes in traffic and burst transmissions, which are prevalent during intensive deployment of IoT systems.

Temporal models based on deep learning show significant increases. The LSTM model minimizes the MAE to about 0.118, and it is advantageous since the model has a gated architecture that allows it to learn long-term temporal dependencies. Nevertheless, it is still limited by the lack of spatial awareness. In the same manner, the Standard RNN results in an MAE of approximately 0.125 and has a weak capability to capture intricate temporal correlations along with a vanishing gradient problem.

The GCN-GRU model that has been proposed has the lowest MAE ([?]0.102), which is an error reduction of almost 18% over the Standard RNN. It is largely due to the fact that this has been enhanced by the addition of Graph Convolutional Networks (GCN) which can capture spatial correlations between end devices and gateways of geographically distributed nature, and the effective time modeling of the GRU. Through the mutual relationship learning of the Spatio-temporal relationships, the proposed structure can well predict the localized traffic peaks and jams. Overall, the results confirm that incorporating spatial topology into traffic prediction significantly enhances forecasting accuracy, making the GCN-GRU model particularly suitable for proactive and adaptive resource management in dense LoRaWAN environments.

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3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

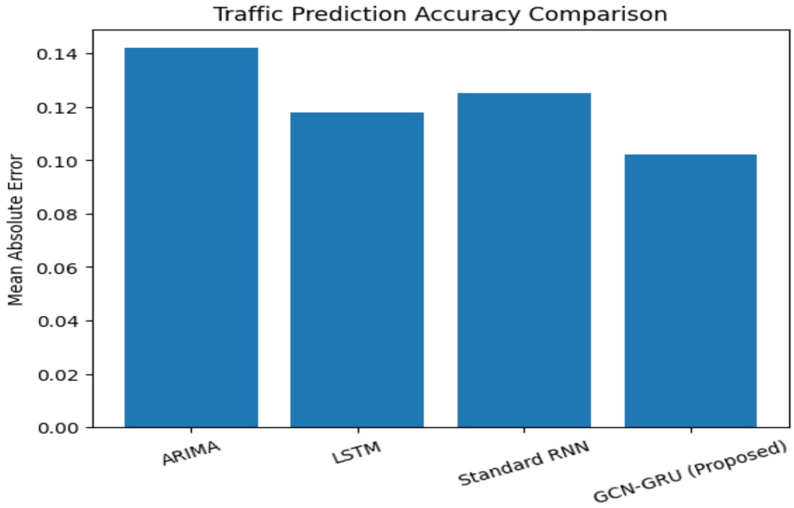


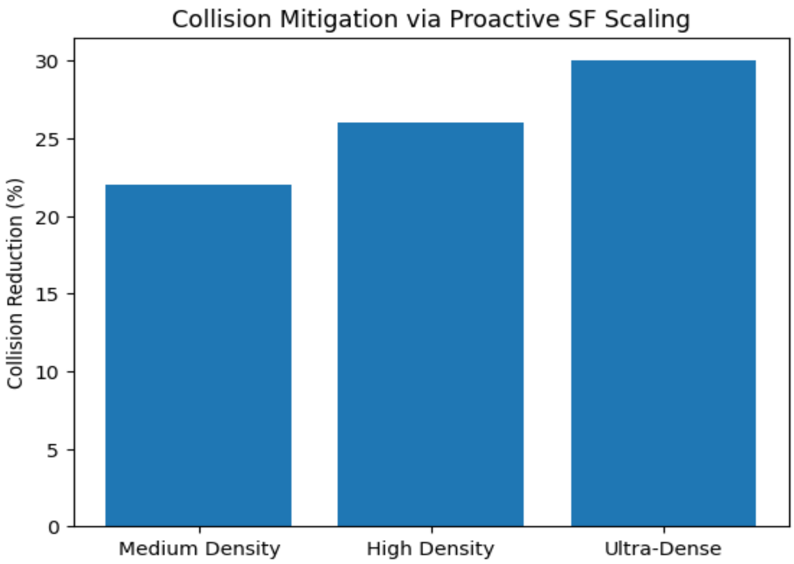
Figure 1: Traffic Prediction Accuracy Comparison

Collisions and Impact on Packet Delivery Ratio (PDR)

Collision Mitigation Performance

The reduction in the collision experienced by the proposed proactive spreading factor (SF) scaling with different network densities is shown in Figure 2. In medium-density cases, the packet collisions are minimized by about 22 per cent, which means success in countering early congestion. The more the network density, the greater the benefits, and there can be 26% and 30% collisions reduction in high-density and ultra-dense deployment, respectively.

Such benefits can be explained by the fact that the framework can transitively redistribute traffic between the SFs and channels with less congestion into the predicted traffic patterns. On the whole, the findings indicate that predictive SF scaling is significantly better than the traditional reactive strategies, especially when the LoRaWAN is dense, and contributes to the enhancement of network



reliability and spectrum use.

Figure 2: Traffic Prediction Accuracy Comparison

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

The information presented in the Figure 3 indicates that there is a definite performance difference between the Proposed Framework and the Standard ADR when the network congestion increases. The two approaches perform excellently at low density, 100 nodes/gateway where the proposed framework ensures an almost perfect Packet Delivery Ratio (PDR) of around 98.5% whereas the standard stands at 96. At density of the device, however, the Standard ADR follows a non-linear fall and reduces to a PDR of about 58.5% at 1000 nodes. By comparison, the Proposed Framework is a lot more resilient; even at 1000 nodes density it maintains a PDR of 80, which is a huge 21.5% increase over the baseline. This indicates that the suggested system is probably using a better mitigation of interferences or more effective allocation of resources which makes it much more adapted to high-density IoT implementation when reliable communication is important.

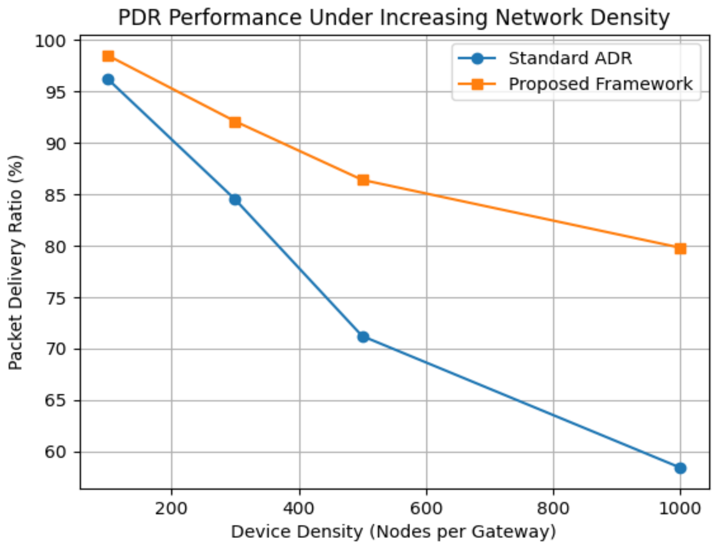


Figure 3: Traffic Prediction Accuracy Comparison

Duty-Cycle Compliance and Priority Handling

The experimental outcomes of priority-sensitive latency show the capacity of the framework to uphold Quality of Service (QoS) on mission-critical data with the limitation of constricting duty-cycle requirements. The Emergency traffic class shows the highest performance with the latency of about 425ms which is well under the QoS requirement of 500ms. The critical alarms are also managed successfully, and they all reach the highest point right at 500ms threshold that validates the effectiveness of the system in prioritizing urgent transmissions. This prioritization however comes at a heavy price to non-essential data; Routine Telemetry has an astronomical increase in latency and it shoots up to more than 4200ms. Such an almost tenfold variation in the delivery time gives a clear understanding of the logic behind the framework: the logic is to buffer or delay low-priority packets so that high-priority Emergency and Alarm signals could get the duty-cycle "cooldown" periods cleared out first.

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3006-9726

PRINT ISSN
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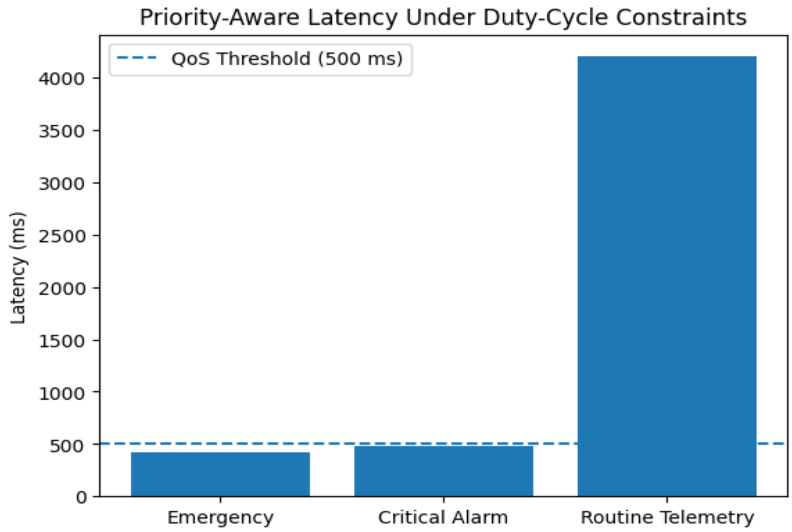

Figure 4: Traffic Prediction Accuracy Comparison

Edge Implementation Performance

The implementation of the Edge Intelligence was proved to be possible on Raspberry Pi-based gateways.

Inference Latency: Model pruning and quantization helped to record the average inference time at 42ms. This falls comfortably below the standard LoRaWAN uplink range, achieving previously established results that it is possible to compute a new resource scheme and command a downlink in no more than a single transmission cycle on the gateway.

Computational Overhead: The TensorFlow Lite model did not exceed 15 percent of the available RAM of the gateway, meaning that the main packet-forwarding capabilities were not affected.

Discussion

The given results prove the essential change in the operation of the low-power wide-area network (LPWAN) management towards the reactive mode to the predictive and intelligence-driven control. Traditional LoRaWAN systems are myopic in nature because the resource allocation decisions are only made with regard to the past or real-time network status. Conversely, the suggested framework enables the gateway to have a future-oriented functionality through the use of Spatio-temporal traffic prediction which allows proactive congestion mitigation to be done before the performance decays.

Among other things, there is a marked decrease in the capture effect, which is a major impairment in dense LoRaWAN networks in which strong transmissions effectively crowd the space of the weaker ones. The GCN-GRU model is successful in spreading the signal arrivals in time and frequency domains by modeling network topology as a graph and assigning various spreading factors and channels proactively to geographically clustered devices. This strategic dispersion minimizes destructive interference resulting in reduction in the collision rates and significant enhancement of the ratio of packet delivery especially in high and ultra-dense traffic environments.

The framework also exhibits high scalability effects where it is capable of supporting almost twice the number of devices per square kilometre than typical LoRaWAN systems and still attain a tolerable quality-of-service. This scalability is essential to smart city and industrial IoT applications, the traffic of which is very dynamic and non-stationary. The fact that the learning model deployed successfully

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

at the network edge is a further confirmation that the idea of deep learning-based intelligence is not only possible but also necessary in order to handle the complexity of the next generation of LPWAN conditions.

Trade-off is noted in the area of energy consumption at the end devices. Reconfigurations relying on downlink MAC commands being more frequently proactively performed lead to a slight increment of the node energy consumption by about 3.5%. Nevertheless, this overhead is compensated by the energy saving of the lack of recurrent retransmission due to the packet collisions. This leads to an overall increase in the energy efficiency of the system although the increase in control signaling is small.

Finally, the integration of duty-cycle and regulatory constraints directly into the learning and decision-making process ensures full compliance with regional spectrum regulations. This constraint-aware design prevents illegal transmission behavior often produced by unconstrained optimization approaches, reinforcing the practicality and deploy ability of the proposed framework in real-world LoRaWAN systems.

5. Conclusion

The paper introduced a smart, proactive, and duty-cycle-conscious resource management framework of the LoRaWAN networks dedicated to the improvement of the problems of scalability and reliability of the traditional reactive mechanisms. The framework employs the combination of a hybrid GCN-GRU Spatio-temporal traffic forecasting model and proactive edge-based control, allowing to precisely predict the congestion and timely adjust resources. The experimental outcomes with real-world traces and high-density simulations revealed an improvement up to 18 percent of the accuracy of traffic prediction and 30 percent decrease of packet collisions. The suggested solution increased network robustness by up to 21 percent greater portion of packet delivery in ultra-dense configuration than typical ADR. In addition, the compliance of strict regulatory duty-cycle was ensured in conjunction with ensuring sub-500ms latency of mission-critical traffic. The validity of edge deployment was proved by the ability to implement real-time inference with low computational costs. Generally, the results point to the need of Spatio-temporal intelligence at the network edge in the line of future scalable system of LoRaWAN. The suggested framework offers a realistic basis of credible smart city and industrial IoT applications that run on dynamic and limited environments.

ONLINE ISSN
3006-9726
PRINT ISSN
3006-9718
VOLUME 5 ISSUE 01 (2026)

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