Traffic Control in 6G-Mobile Internet of Things Using Recurrent Neural Networks and Fuzzy Logic

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4 authors:


Seyed Salar Sefati
Polytechnic University of Bucharest


Ahmed Nor
Polytechnic University of Bucharest


Octavian Fratu
Polytechnic University of Bucharest


Simona Halunga
Electronics Telecommunications and Information Technology Faculty

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Seyed Salar Sefati
Telecommunications Department
National University for Science and Technology POLITEHNICA Bucharest
Bucharest, Romania
sefati.seyedsalar@upb.ro

Ahmed M. Nor
Telecommunications Department
National University for Science and Technology POLITEHNICA Bucharest
Bucharest, Romania
ahmed.nor@upb.ro

Octavian Fratu
Telecommunications Department
National University for Science and Technology POLITEHNICA Bucharest
Bucharest, Romania
octavian.fratu@upb.ro

Simona Halunga
Telecommunications Department
National University for Science and Technology POLITEHNICA Bucharest
Bucharest, Romania
simona.halunga@upb.ro

***Abstract*—The Mobile Internet of Things (MIoT) refers to a network of interconnected, internet-enabled devices that can communicate and share data together through mobile and wireless networks. This paper presents a novel framework for congestion management in MIoT networks by integrating Long Short-Term Memory (LSTM) networks with fuzzy logic to enhance predictive and adaptive decision-making capabilities for 6G networks. With the proliferation of MIoT devices, network congestion is becoming increasingly problematic, necessitating advanced solutions to maintain efficient data flow and network stability. The approach begins with systematic data collection, capturing essential traffic metrics. This data undergoes to a preprocessing step to facilitate Long Short-Term Memory (LSTM) analysis, focusing on normalization and time-series structuring. The LSTM models are trained to accurately predict traffic patterns, employing strategies such as regularization and dropout to prevent overfitting and enhance model reliability. Subsequently, a fuzzy logic system interprets these predictions, applying a set of linguistic rules to refine the forecasts further. This methodology enables dynamic, proactive management of network congestion, and improves data transmission efficiency and network resource optimization.**

***Index Terms*—Congestion Management, LSTM, Fuzzy Logic, Network Traffic Management, Mobile Internet of Things**

I. Introduction

Mobile Internet of Things (MIoT) represents the convergence of two powerful technologies: mobile connectivity and the Internet of Things (IoT) [1]. MIoT enables a vast array of devices, sensors, and objects to communicate seamlessly, facilitating real-time data exchange and remote control. This empowers diverse applications, e.g., smart homes and cities, industrial automation, and healthcare. With MIoT, devices can communicate autonomously, providing valuable insights, optimizing processes, and enhancing efficiency, while offering unprecedented convenience and connectivity levels [2]. Congestion control is a crucial aspect of network management, employed to ensure efficient data flow and prevent overload [3]. It encompasses various techniques and algorithms aimed at regulating the rate of data transmission to maintain optimal performance and prevent network congestion. By dynamically adjusting data transmission rates based on network conditions, congestion control mechanisms mitigate packet loss, reduce latency, and ensure fair allocation of network resources. Through techniques such as packet prioritization, traffic shaping, congestion avoidance algorithms like Transmission Control Protocol (TCP) [4], and congestion control mechanisms, networks can manage traffic loads, optimize throughput, and maintain overall stability, thereby enhancing the reliability and performance of communication systems.

6G, the highly anticipated next generation of wireless communication technology, is poised to revolutionize connectivity by offering unprecedented speed, capacity, and reliability. This innovative leap builds upon the achievements of its predecessors, aiming to transcend existing limitations and pave the way for a hyper-connected era where virtually every aspect of daily life is seamlessly integrated into digital networks. To meet the evolving demands of this landscape, advanced algorithms such as Long Short-Term Memory (LSTM) and fuzzy logic [5] are being integrated, foreseeing the requirements of next-generation IoT environments. This integration ensures adaptability and efficiency in managing congestion amidst the increasingly intricate and dynamic network conditions expected in the 6G era. The proposed methodology presents a comprehensive approach to congestion management in IoT networks, comprising several distinct steps. Initially, data collection organizes crucial metrics such as packet transmission rates, sizes, and timestamps into a structured dataset. Subsequently, preprocessing techniques normalize and structure the data into time-series formats, preparing it for further analysis. Fuzzy logic systems are then employed to handle uncertainties

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and subjective assessments, defining linguistic variables and establishing rules for congestion prediction. Finally, recurrent neural networks (RNNs) [6], particularly Long Short-Term Memory (LSTM) networks, are trained to forecast future traffic patterns based on historical data, ensuring proactive congestion management strategies in 6G-enabled IoT networks.

The contributions of this paper are: First, to address congestion management in IoT networks, an integrated approach using RNNs and fuzzy logic is presented in the paper. Seconddly, to enable proactive management, dynamic congestion prediction with LSTM networks is introduced. Finally, to enhance decision-making adaptability for congestion management in IoT networks, fuzzy logic is employed.

II. Related work

The authors in [7] present a method for enhancing urban traffic management. This research highlights the use of smartphones and onboard sensors to gather traffic data in real time to provide effective traffic control solutions. The work in [8] introduces a novel cluster-based congestion-mitigating access scheme (CCAS) designed to address severe collision and congestion issues in machine-type communication (MTC). This work leverages modified spectral clustering algorithms and queuing theory to optimize the access performance, significantly reducing collision probabilities and access delays, while accommodating massive simultaneous device connections. Also, it enhances system efficiency and supports the diverse service requirements of various MTC applications.

The authors in [9] introduce an innovative congestion control mechanism for IoT applications using the Constrained Application Protocol. This algorithm applies deep reinforcement learning (DRL) to dynamically manage network congestion by calculating optimal retransmission timeouts. The algorithm demonstrates improvements in throughput, packet delivery ratios, and energy efficiency compared to standard protocols. In [10], congestion management is addressed in Medical IoT systems. This protocol enhances network throughput, reduces delays, and improves energy efficiency by adapting data transmission priorities during emergencies, thereby ensuring reliable and timely delivery of vital patient data.

The work in [11] focuses on improving data flow in IoT networks through the Routing Algorithm optimization over Network Clustered. It leverages network performance metrics like throughput, packet loss, and energy consumption, showing significant improvements through NS2 simulations. The authors in [12] present a congestion control strategy utilizing clustering and hierarchical structures in Wireless Sensor Networks. It introduces the Imperialist Competitive Algorithm (ICA) for efficient cluster formation and selection of master nodes to manage data transmission, aiming to optimize packet delivery rate, throughput, and reduce energy consumption.

III. Proposed Methodology

A. Problem statement

Addressing the congestion conundrum necessitates a robust framework capable of preemptively identifying, mitigating, and ideally circumventing network bottlenecks, while also accommodating the anticipated surge in connected devices and data traffic characteristic of 6G networks [13]. As MIoT devices proliferate, the exponential surge in data transmission demands not only strains existing infrastructure but also threatens to impede critical communication pathways essential for the seamless operation of 6G networks. Thus, the imperative lies in devising a comprehensive strategy that harmonizes device interactions, optimizes bandwidth allocation, and fosters seamless data exchange, thereby fostering the uninterrupted evolution of the MIoT ecosystem within the overarching 6G network landscape. The paper aims to address these challenges by proposing a novel approach combining RNN algorithm and fuzzy logic-based decision-making tailored for the demands of 6G MIoT networks. It presents a multi-step methodology encompassing data collection, preprocessing, LSTM network training, and fuzzy logic system setup, all intricately designed to handle the unique complexities of 6G MIoT environments.

B. QoS Formulas for MIoT

Reliability in MIoT can be defined as the probability that a system will operate correctly and deliver the intended functionality over a specified period and under given conditions.

$$R = 1 - \prod_{i=1}^{n}(1 - r_i) \tag{1}$$

where R is the overall system reliability, r_i represents the reliability of the i^{th} component or subsystem, and n is the total number of components or subsystems in the system.

Energy consumption refers to the total amount of electrical energy consumed by devices, sensors, and communication infrastructure during their operation.

$$E = P \times t \tag{2}$$

where E is the energy consumption, P is the power consumption rate, and t is the time duration.

Latency, also known as response time, is the time interval between the initiation of a data transfer request and the receipt of the corresponding response.

$$L = \frac{d}{v} \tag{3}$$

where L is the latency, d is the distance sent of data, and v is the velocity of data transmission.

C. Proposed method

Step 1: Data Collection The data collection process is formalized as follows

$$D = \{(r_i, s_i, t_i) \mid i \in \mathcal{I}\} \tag{4}$$

where D represents the set of collected data points. r_i denotes the packet transmission rate of the i-th IoT device, measured in packets per second (pps). s_i represents the size of packets transmitted by the i-th device, measured in bytes. t_i is the timestamp of the data collection for the i-th device, indicating the exact time the data was recorded. $\mathcal{I}$ is the index set of all IoT devices participating in the data collection, $\mathcal{I} = \{1, 2, \ldots, n\}$, where n is the total number of devices.

Step 2: Preprocessing The process starts with Min-Max Scaling, followed by the organization of data into a structured matrix format suitable for RNN input.

Normalization: The Min-Max Scaling for each feature j in the dataset is given by

$$x_{\text{norm}}^{(j)} = \frac{x^{(j)} - \min(x^{(j)})}{\max(x^{(j)}) - \min(x^{(j)})} \tag{5}$$

where $x^{(j)}$ represents the j-th feature vector of raw data, and $\min(x^{(j)})$ and $\max(x^{(j)})$ are the minimum and maximum values of the j-th feature, respectively.

Time-Series Structuring: The data is structured into sequences to be processed by the RNN. This is represented as

$$\mathbf{X}_{\text{seq}} = \begin{bmatrix} \vec{x}_1 & \vec{x}_2 & \ldots & \vec{x}_T \end{bmatrix}^\top \tag{6}$$

Here, $\vec{x}_t$ denotes the vector of normalized features at time t, for $t = 1, 2, \ldots, T$, where T is the sequence length. Each row in $\mathbf{X}_{\text{seq}}$ corresponds to a time step, encapsulating all features at that particular time. The vectors $\vec{x}_t$ and matrix $\mathbf{X}_{\text{seq}}$ illustrate the application of linear algebra to handle multi-dimensional data systematically.

Step 3: Fuzzy Logic System Setup The fuzzy logic system is configured to handle uncertainties and subjective assessments in traffic load and priority. This step involves defining linguistic variables, establishing rules, and implementing a fuzzy inference system to predict congestion levels.

Defining Linguistic Variables: For traffic analysis, the system variables, that categorize traffic load and priority levels, are defined as:

$$\text{Traffic Load: } \{\text{Low, Medium, High}\}$$

$$\text{Priority: } \{\text{Low, Medium, High}\}$$

These linguistic terms are associated with fuzzy sets on the universe of discourse, typically representing traffic metrics such as bandwidth usage or packet counts.

Establishing Fuzzy Rules: Fuzzy rules form the inference mechanism. A typical rule might look like: If (Traffic Load is High) and (Priority is Low) then (Congestion is High)

Fuzzy Inference System: processes inputs through these rules to derive an output. This step is crucial for real-time assessment and proactive management of resources to prevent or mitigate congestion. In our approach, the output is

$$\text{Congestion Level: } \{\text{Low, Moderate, High}\}$$

Step 4: RNN Model Training LSTM Network Configuration: The configuration of an LSTM for predicting future traffic patterns involves setting up network architecture that typically includes, first, input layer, corresponding to the number of features in the traffic data (e.g., packet rates, sizes). Second, LSTM layers, where the number of LSTM units in each layer is a hyperparameter that affects the model's complexity and capacity. Finally, an output layer, which predicts future traffic conditions based on learned patterns.

Training the LSTM Network: The training process is guided by a loss function, which measures the discrepancy between the predicted traffic patterns and the actual observed data. The chosen loss function is the Root Mean Squared Error (RMSE), formulated as:

$$\text{Loss Function: } \mathcal{L}(y, \hat{y}) = \sqrt{(y - \hat{y})^2} \tag{7}$$

where y represents the actual observed traffic data, $\hat{y}$ is the predicted traffic data output by the LSTM, and $\mathcal{L}(y, \hat{y})$ quantifies the prediction error, serving as the objective to be minimized during training.

To minimize the loss function $\mathcal{L}(y, \hat{y})$, optimization algorithms adjust the LSTM network's weights $\mathbf{W}$. The update rule for Stochastic Gradient Descent (SGD) is given by:

$$\mathbf{W}_{\text{new}} = \mathbf{W}_{\text{old}} - \eta \nabla \mathcal{L}(\mathbf{W}_{\text{old}}) \tag{8}$$

where $\mathbf{W}_{\text{old}}$ and $\mathbf{W}_{\text{new}}$ are the weight matrices before and after the update, respectively. η is the learning rate and $\nabla \mathcal{L}(\mathbf{W}_{\text{old}})$ is the gradient of the loss function with respect to the weights. We use Adam optimizer, hence the update rule incorporates moment estimates:

$$\mathbf{W}_{\text{new}} = \mathbf{W}_{\text{old}} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{9}$$

where $\hat{m}_t$ and $\hat{v}_t$ are bias-corrected first and second moment estimates of the gradients, and ϵ is a small constant to avoid division by zero.

To prevent over-fitting, we define

$$\text{Regularization: } \mathcal{L}_{\text{reg}}(y, \hat{y}, \mathbf{W}) = \mathcal{L}(y, \hat{y}) + \lambda \|\mathbf{W}\|^2 \tag{10}$$

where λ is the regularization parameter, and $\|\mathbf{W}\|^2$ represents the L2 norm of the weight matrix.

Dropout is applied during training by randomly omitting a subset of features or neurons.

Model Validation: is assessed using a validation loss:

$$\mathcal{L}_{\text{val}}(y_{\text{val}}, \hat{y}_{\text{val}}) = \sqrt{(y_{\text{val}} - \hat{y}_{\text{val}})^2} \tag{11}$$

where y_{val} and $\hat{y}_{\text{val}}$ are the actual and predicted values on the validation dataset, respectively.

Step 5: Congestion Prediction

This step involves utilizing both the LSTM network and the fuzzy logic system to predict and refine congestion levels. The methodology is based on inputting current and historical data into the LSTM to predict future states, which are then adjusted using the outputs from the fuzzy logic system.

LSTM Prediction: The LSTM network is fed with current and historical traffic data to forecast short-term future congestion. The prediction is formulated as:

$$\hat{y}_{\text{future}} = \text{LSTM}(\mathbf{X}_{\text{current}}, \mathbf{X}_{\text{historical}}) \tag{12}$$

where $\mathbf{X}_{\text{current}}$ and $\mathbf{X}_{\text{historical}}$ represent the matrices of current and historical traffic data, respectively. $\hat{y}_{\text{future}}$ is the LSTM's output, predicting future congestion levels.

Combination with Fuzzy Logic: To refine the LSTM's predictions and incorporate expert knowledge and rule-based reasoning, the fuzzy logic system is employed. The fuzzy logic system takes the LSTM's output and adjusts it based on defined rules and membership functions:

$$y_{\text{refined}} = \text{FuzzyLogic}(\hat{y}_{\text{future}}, \text{Rule Set}) \tag{13}$$

where Rule Set contains fuzzy rules such as "If congestion is high and time is peak hours, then increase congestion level". y_{refined} is the final congestion prediction, considering both quantitative predictions and qualitative rules.

Step 6: Decision Making Based on the refined predictions of congestion levels from the previous step, the system calculates optimal routes and resource allocation strategies to manage and mitigate potential congestion. This process can be mathematically represented by an optimization problem:

$$\min_{r,a} \sum_{i=1}^{N} c_i(r_i, a_i) \tag{14}$$

where r_i and a_i denote the routing path and resource allocation for the i-th IoT device. $c_i(r_i, a_i)$ is the cost function associated with the i-th device, which may include factors like latency, energy consumption, and reliability.

Fuzzy Decision-Making: We use fuzzy logic to evaluate multiple criteria and make decisions as

$$\text{Decision}(y_{\text{refined}}) = \text{FuzzySystem}(y_{\text{refined}}, \text{Criteria})$$

where y_{refined} includes the fuzzy-adjusted congestion levels. Criteria include factors such as minimum impact on service quality, cost, and system resilience. FuzzySystem represents the decision-making process that integrates these criteria to formulate the most suitable routing and allocation strategies.

Application of Fitness Function: Integrate the fitness function to assess the effectiveness of each potential strategy:

$$\text{Fitness}(R, L, E) = \alpha \cdot \frac{1}{1+e^{-R}} + \beta \cdot \frac{1}{L} + \gamma \cdot \frac{1}{E} \tag{15}$$

R is the reliability score derived from network performance metrics. L represents the average latency measured during peak usage. E is the energy consumption of the IoT devices and network infrastructure. α, β, γ are weighting factors optimized to prioritize different aspects of the network performance based on current network goals and conditions.

Step 7: Control Signal Dispatch Upon determining the optimal routing and resource allocation strategies, control signals are dispatched to the IoT devices to adjust their transmission rates and routing paths to effectively manage network congestion. This process can be mathematically represented as

$$\text{Dispatch}(\mathbf{u}, \mathbf{r}) = \begin{cases} u_i \to \text{Device}_i & \text{for rate adjustment} \\ r_i \to \text{Device}_i & \text{for route adjustment} \end{cases}$$

where $\mathbf{u} = \{u_1, u_2, \ldots, u_N\}$ represents the set of new transmission rates assigned to each IoT device. $\mathbf{r} = \{r_1, r_2, \ldots, r_N\}$ denotes the set of routing paths allocated to each device. Device_i is the i-th IoT device receiving the updated control signal.

Signal Transmission and Monitoring: The control signals are transmitted via a secure network protocol to ensure timely and accurate updates to each device. Following the dispatch, the system continuously monitors the impact of these adjustments on the network to evaluate their effectiveness and make necessary updates in real-time.

Feedback Integration: The feedback from the devices post adjustment is crucial for learning and adaptation. This feedback is used to further refine the decision-making algorithms and enhance future predictions and optimizations:

Update(Feedback) = Algorithm Adjustment (Historical Data, Feedback)

This feedback loop helps in dynamically adjusting the system to changes and maintaining optimal network performance under varying conditions.

IV. Experimental results

In the proposed algorithm, the topology configuration begins with nodes evenly distributed throughout a predefined area. Following this, the evolutionary imperialist competitive algorithm clusters these dispersed nodes. For the MIoT simulations, the parameters are meticulously set up: the first scenario utilizes an area of 200 x 200 square meters, includes 100 uniformly distributed sensors, each with a radio range of 25 meters, an initial energy of 1 joule, electronic energy consumption at 50 nanojoules per bit, amplifier energy consumption at 10 picojoules per bit per square meter, a buffer size of 65 bytes, a packet size of 128 bytes, and a transmission rate of 512 bytes per cycle, based on four packets of 128 bytes each. The second scenario expands the environment to 1000 x 1000 square meters and increases the radio range to 100 meters to ensure effective communication across the larger area. In the proposed method, comparisons are conducted with the CCAS [8] and the ICA [12].

Fig. 1 depicts the energy consumption of the proposed method alongside ICA and CCAS across various transmission rates (128, 256, 512, 1024). The proposed system demonstrates a consistently lower energy footprint, an critical attribute for sustainable IoT deployments. The gradual increment in energy consumption with higher transmission rates underscores the efficiency of the proposed model, particularly in energy-constrained environments. Fig. 2 illustrates the average reliability percentage of data transmission in IoT networks. The proposed system exhibits high reliability that is comparable to ICA and CCAS at lower transmission rates. A marginal decline in reliability at the highest transmission rate (1024) suggests a trade-off between throughput and reliability, yet the system maintains a commendable performance threshold. Fig. 3 presents the transmission delay in milliseconds (ms), which is a pivotal parameter for real-time IoT applications. The proposed method outshines the comparative systems by maintaining lower delay intervals, emphasizing its capability to facilitate timely data transmission which is paramount in time-sensitive IoT applications.

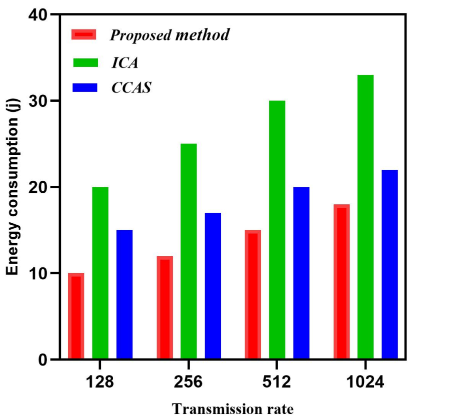

Fig. 1. Energy Consumption by Transmission Rate

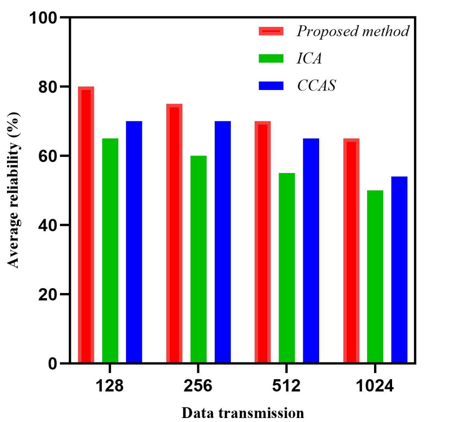

Fig. 2. Average Reliability of Data Transmission

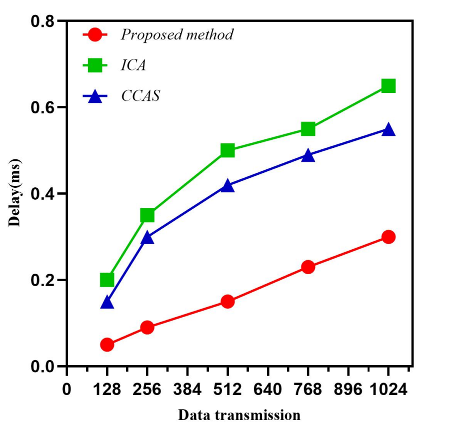

Fig. 3. Delay in Data Transmission

V. Conclusion

This paper presents an innovative framework for managing congestion in MIoT networks, utilizing a combination of LSTM and fuzzy logic. LSTM is used to predict traffic flow, while fuzzy logic is employed to adaptively manage congestion, thereby improving network efficiency and stability. The framework processes traffic data through normalization and LSTM analysis, followed by fuzzy logic refinement for precise congestion control. Results show significant enhancements in reducing energy consumption, increasing reliability, and lowering latency. This research sets a foundation for future advancements in IoT network optimization.

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