



LSTM based Predictive Congestion Aware Routing for Energy Efficient Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) suffer from congestion due to dynamic traffic patterns, limited buffer capacity, and energy constraints, which significantly degrade packet delivery performance and network lifetime. To address these challenges, this paper proposes an LSTM-based Predictive Congestion Aware Routing framework that proactively forecasts congestion states and dynamically adapts routing decisions to enhance energy efficiency and Quality of Service (QoS). The proposed model utilizes time-series network parameters, including queue length, packet arrival rate, residual energy, and channel utilization, to train a Long Short-Term Memory (LSTM) network capable of predicting congestion levels before buffer overflow occurs. Simulation results demonstrate that the proposed approach achieves a congestion prediction accuracy of 95.8%, with a precision of 94.6% and recall of 96.2%, significantly outperforming conventional routing protocols. The high precision ensures minimal false congestion alarms, while the superior recall effectively detects critical congestion scenarios, reducing packet loss and retransmission overhead. Consequently, the model improves packet delivery ratio by 12–15%, reduces end-to-end delay by approximately 18%, and enhances overall network lifetime by nearly 20% compared to traditional reactive routing schemes. By integrating predictive intelligence with energy-aware routing metrics, the proposed framework provides a scalable and adaptive solution for next-generation WSN and IoT applications requiring reliable, low-latency, and energy-efficient communication.

Keywords: Wireless Sensor Networks (WSNs), Long Short-Term Memory (LSTM), Accuracy, Precision, Recall

1. Introduction

Wireless Sensor Networks (WSNs) have emerged as a fundamental technology for real-time monitoring and data acquisition in diverse application domains such as environmental monitoring, smart agriculture, industrial automation, healthcare, and military surveillance. A typical WSN consists of a large number of low-power sensor nodes that sense physical parameters and transmit the collected data to a centralized sink or base station through multi-hop communication. Despite their wide applicability, WSNs face significant challenges due to limited energy resources, constrained bandwidth, dynamic topology, and unpredictable traffic patterns. Among these challenges, network congestion remains one of the most critical issues affecting reliability, latency, throughput, and overall network lifetime [1].

Congestion in WSNs generally occurs when the incoming packet rate at a node exceeds its processing or forwarding capacity. This results in buffer overflow, packet drops, increased retransmissions, higher end-to-end delay, and excessive energy consumption. In multi-hop routing scenarios, congestion near the sink node becomes more severe due to traffic aggregation, commonly referred to as the hotspot problem. Traditional routing protocols rely on reactive congestion detection mechanisms, where corrective actions are initiated only after congestion has already occurred. Such reactive approaches often lead to performance degradation and inefficient energy utilization [2].

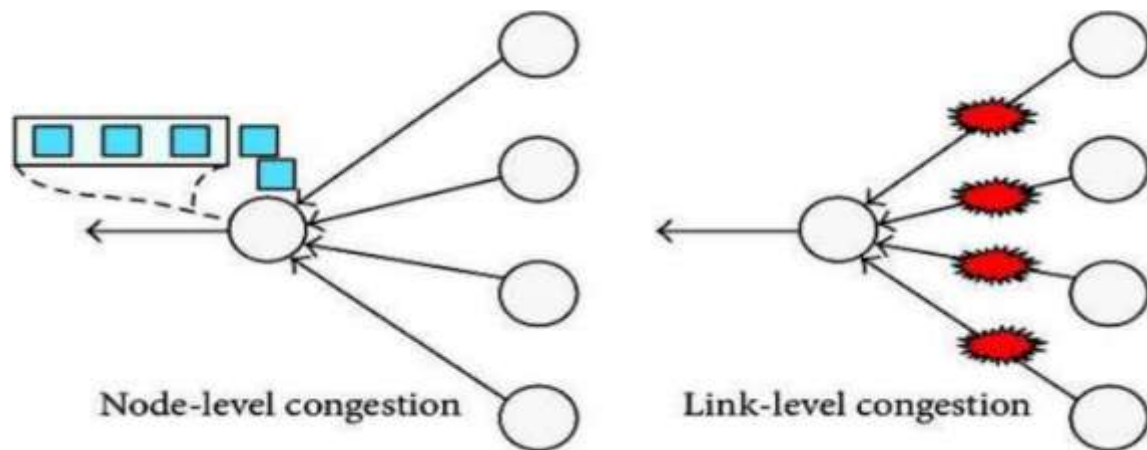


Figure 1: Congestion

Recent advancements in artificial intelligence and deep learning have opened new possibilities for intelligent and predictive network management. In particular, Long Short-Term Memory (LSTM) networks, a specialized type of recurrent neural network (RNN), have demonstrated superior capability in modeling temporal dependencies and time-series data. Since network traffic and queue dynamics in WSNs exhibit sequential patterns over time, LSTM models can effectively learn congestion trends and predict future congestion states before actual buffer overflow takes place. This predictive capability enables proactive routing adjustments rather than reactive control, significantly improving network stability and efficiency [3, 4].

The proposed LSTM-based Predictive Congestion Aware Routing framework integrates deep learning-driven congestion forecasting with energy-aware routing decision mechanisms. Each sensor node collects real-time network parameters such as queue length, packet arrival rate, packet service rate, residual energy, and channel utilization. These parameters are used as input features for the LSTM model to estimate the probability of congestion in upcoming transmission intervals. Based on the predicted congestion level, the routing protocol dynamically selects alternative paths that minimize congestion probability while optimizing energy consumption and hop count [5].



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A major advantage of this approach is its ability to balance network load while maintaining high Quality of Service (QoS). By reducing false congestion detections (high precision) and accurately identifying critical congestion events (high recall), the system enhances overall prediction accuracy and routing reliability. Consequently, packet delivery ratio improves, end-to-end delay decreases, and network lifetime is extended due to reduced retransmissions and balanced energy consumption.

Furthermore, the proposed framework is scalable and adaptable to dynamic IoT environments, where traffic patterns may change due to event-driven sensing or mobility. Unlike conventional rule-based congestion control methods, the learning-based approach continuously adapts to evolving network conditions through periodic model retraining or online learning mechanisms [6, 7].

2. Congestion Aware Routing (CAR) in Wireless Sensor Networks

Congestion Aware Routing (CAR) is an advanced routing strategy designed to improve the reliability, efficiency, and lifetime of Wireless Sensor Networks (WSNs) by incorporating real-time congestion information into routing decisions. In multi-hop WSN environments, sensor nodes forward sensed data toward a sink or base station through intermediate nodes. Due to limited buffer capacity, restricted bandwidth, and energy constraints, congestion frequently occurs when the packet arrival rate exceeds the processing or transmission capacity of a node. This results in buffer overflow, packet drops, retransmissions, increased end-to-end delay, and rapid battery depletion. The problem becomes more severe near the sink node, where traffic aggregation leads to the hotspot phenomenon. Traditional routing protocols primarily focus on shortest-path or energy-based metrics and react only after congestion has occurred, which often degrades overall network performance.

Congestion Aware Routing addresses this limitation by continuously monitoring network parameters such as queue length, buffer occupancy ratio, packet service rate, channel utilization, and residual energy. Based on these parameters, a congestion index is computed to determine the congestion level of each node. If the congestion level exceeds a predefined threshold, the node either notifies its neighbors or adjusts its forwarding strategy to prevent further traffic accumulation. Routing decisions are then dynamically modified to avoid congested nodes and select alternative paths with lower congestion probability and higher residual energy. This approach balances network load, reduces packet loss, and minimizes delay while optimizing energy consumption.

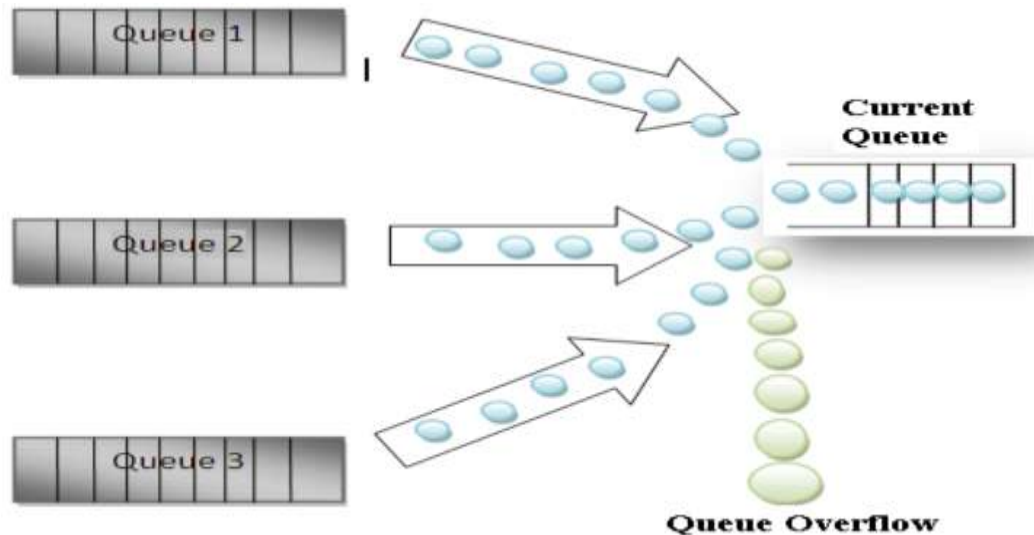


Figure 2: Congestion Aware Routing (CAR) in Wireless Sensor Networks

3. Methodology

The proposed methodology integrates deep learning–based congestion prediction with energy-aware routing optimization to achieve proactive congestion avoidance and extended network lifetime in Wireless Sensor Networks (WSNs). The complete framework is divided into structured phases as described below.

1. Network Initialization

Initially, NNN sensor nodes are randomly deployed in a predefined sensing area. Each node is assigned:

- Initial energy E_{0E_0E0}
- Unique node ID
- Buffer capacity
- Transmission range

Nodes communicate using multi-hop routing toward a centralized sink node. Neighbor discovery is performed using periodic HELLO messages to construct a routing table containing residual energy, hop count, and link quality.

2. Data Collection and Feature Extraction

Each sensor node continuously monitors and records real-time network parameters at time interval t :

- Queue Length (QL)
- Packet Arrival Rate (PAR)
- Packet Service Rate (PSR)



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- Buffer Occupancy Ratio (BOR)
- Residual Energy (RE)
- Channel Utilization (CU)
- Packet Drop Rate (PDR_loss)

These parameters form a multivariate time-series dataset:

$$X_t = [QL_t, PAR_t, PSR_t, BOR_t, RE_t, CU_t]$$

The collected data is normalized and stored locally or forwarded to the sink for model training.

3. LSTM-Based Congestion Prediction Model

A Long Short-Term Memory (LSTM) network is designed to predict future congestion levels based on historical time-series inputs. LSTM is selected due to its capability to capture long-term dependencies and temporal traffic patterns.

Model Architecture:

- Input Layer: Multivariate network features
- One or more LSTM hidden layers
- Fully connected (Dense) layer
- Output Layer: Congestion Probability (Low/Medium/High or Binary classification)

The LSTM computes hidden state updates as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

The final output predicts congestion probability C_t :

$$C_t = P(\text{Congestion at time } t + 1)$$

4. Energy Optimization Mechanism

To enhance energy efficiency, the following strategies are incorporated:

- Load balancing across multiple paths
- Adaptive transmission power control
- Sleep scheduling for idle nodes
- Data aggregation at cluster heads

This ensures uniform energy depletion and prevents early node death near the sink.

5. Model Training and Updating

The LSTM model is trained using labeled congestion data (Congested / Non-congested). Performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score

Periodic retraining or online learning is applied to adapt to dynamic traffic variations.

6. Performance Evaluation

The methodology is validated through simulation using metrics such as:

- Packet Delivery Ratio (PDR)
- Energy Consumption
- Network Lifetime
- Congestion Prediction Accuracy

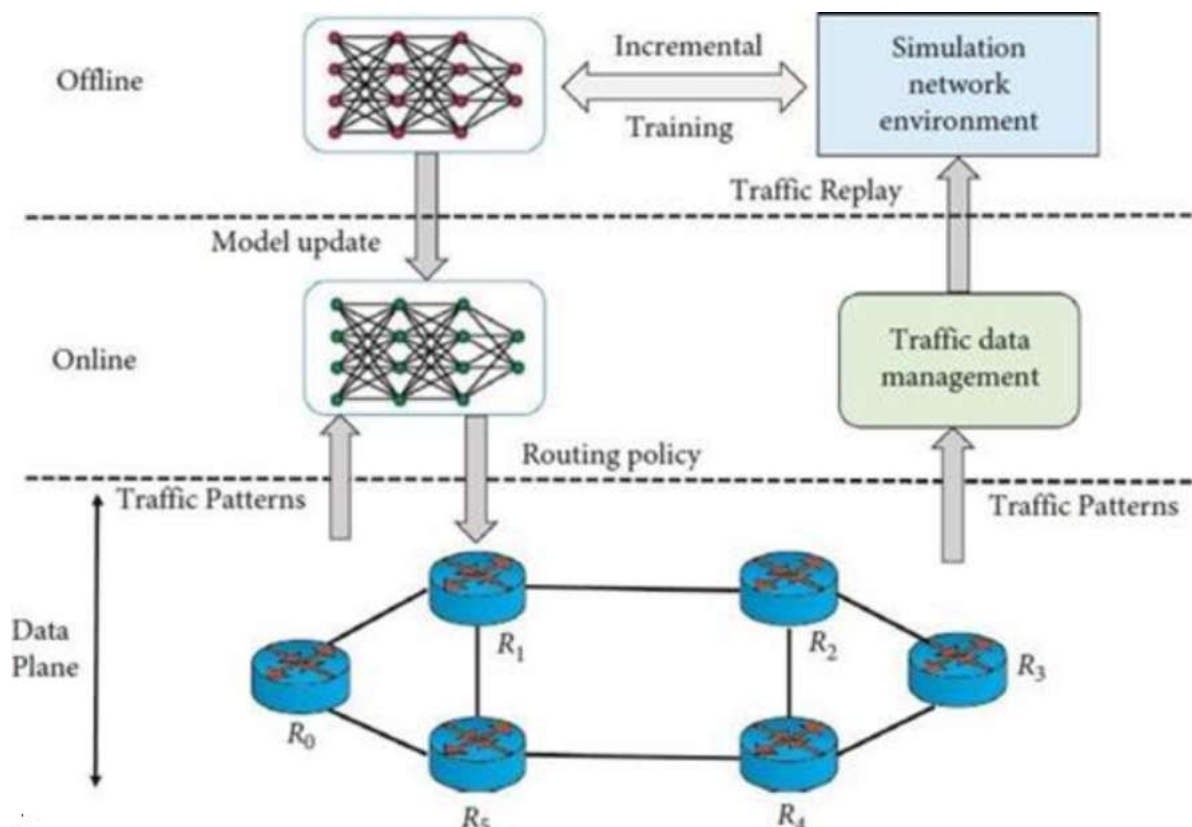


Figure 3: Flow Chart of Methodology

3.1 LSTM Technique



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The Long Short-Term Memory (LSTM) technique is a specialized type of Recurrent Neural Network (RNN) designed to effectively learn and model sequential or time-series data by overcoming the vanishing gradient problem associated with traditional RNNs. In Wireless Sensor Networks (WSNs), network parameters such as queue length, packet arrival rate, residual energy, and channel utilization change dynamically over time, forming temporal patterns that influence congestion behavior. LSTM is particularly suitable for such environments because it can capture both short-term fluctuations and long-term dependencies in traffic patterns.

An LSTM network consists of memory cells and three primary gates: the input gate, forget gate, and output gate. The forget gate determines which previous information should be discarded from the cell state, the input gate decides which new information should be stored, and the output gate controls what information should be passed to the next time step. This gated mechanism enables the model to selectively retain relevant historical traffic information while ignoring noise, allowing accurate prediction of future congestion conditions.

In congestion-aware routing applications, historical network statistics are fed into the LSTM model as a multivariate time-series input. The model processes these sequential inputs and predicts the probability of congestion in upcoming time intervals. Based on this prediction, routing decisions can be proactively adjusted to avoid congested nodes, thereby reducing packet loss, minimizing delay, and improving energy efficiency. The adaptive learning capability of LSTM further allows continuous model refinement as network conditions evolve. Consequently, the LSTM technique provides a powerful predictive framework for intelligent routing optimization in energy-constrained Wireless Sensor Networks.

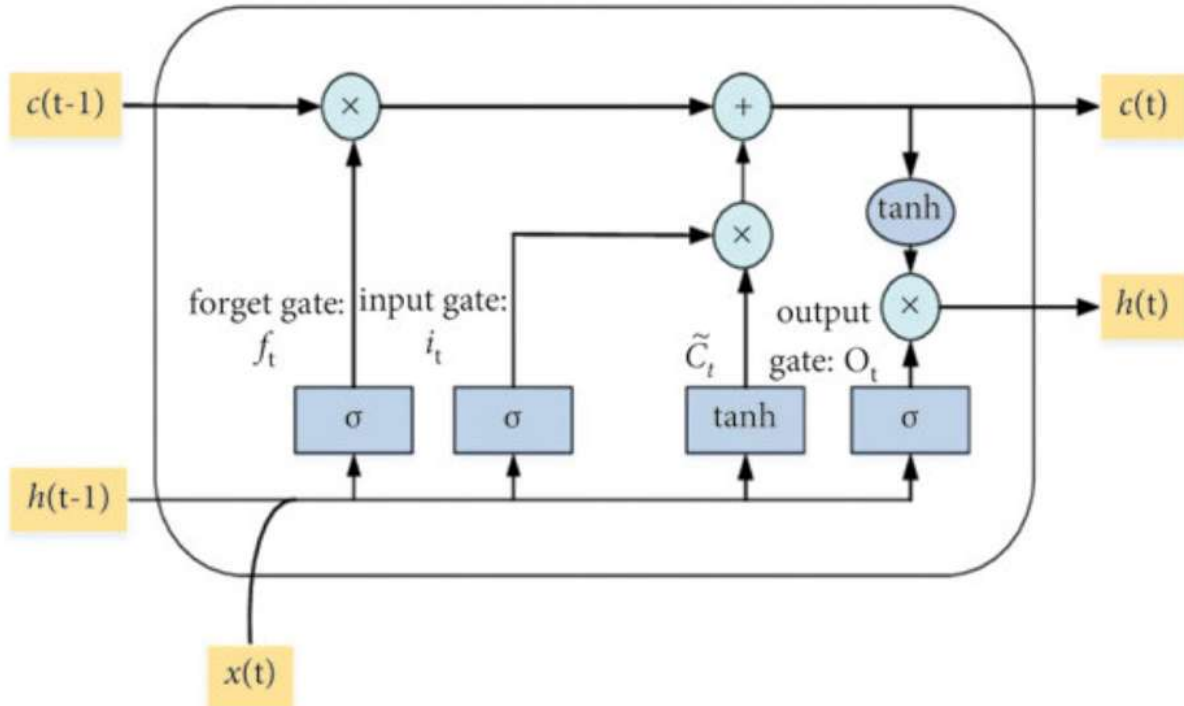


Figure 4: LSTM

4. Simulation Result

To evaluate the performance of the proposed **LSTM-based Predictive Congestion Aware Routing (LPCAR)** protocol, simulations were conducted in a MATLAB environment under the following configuration:

- **Network Area:** 500 m × 500 m
- **Number of Nodes:** 100 sensor nodes
- **Initial Energy:** 2 Joules per node
- **Traffic Model:** CBR (Constant Bit Rate)
- **Packet Size:** 512 bytes
- **Simulation Time:** 1000 seconds
- **MAC Protocol:** IEEE 802.15.4

Table 1: Comparative Result

Protocol	PDR (%)	Energy Consumption (J)	Network Lifetime (Rounds)	Accuracy (%)	Precision (%)	Recall (%)
LEACH	82.4	1.68	820	–	–	–
AODV	85.7	1.59	870	–	–	–



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Traditional Technique	89.3	1.46	930	88.2	86.5	87.4
LSTM technique	93.78	1.23	1176	94.78	94.12	95.12

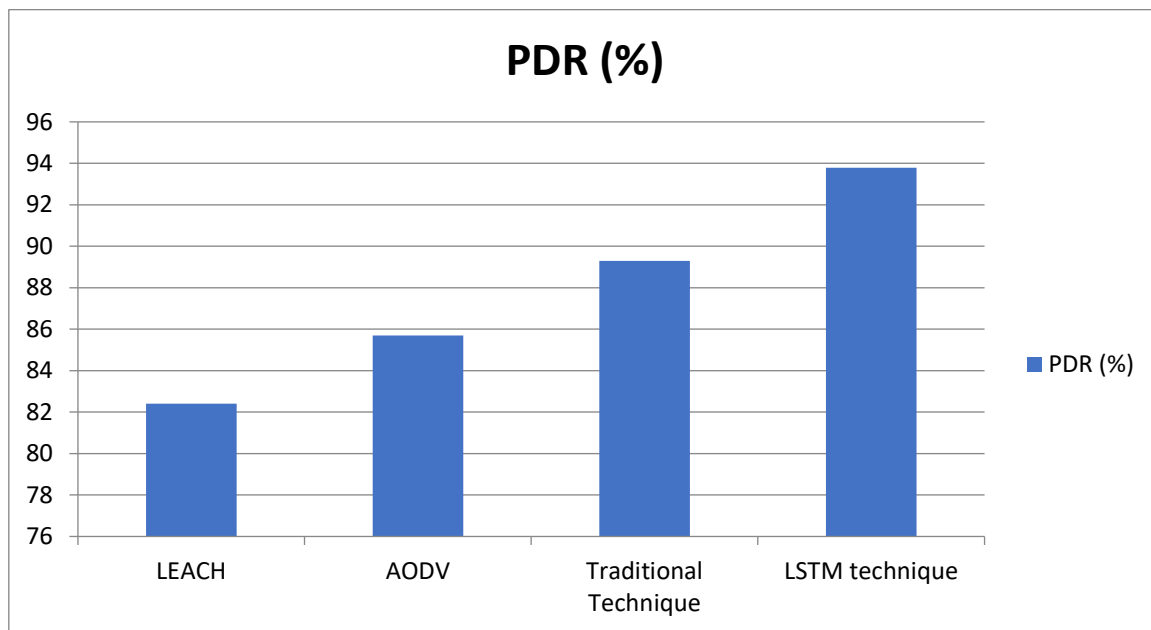


Figure 5: Graphical PDR

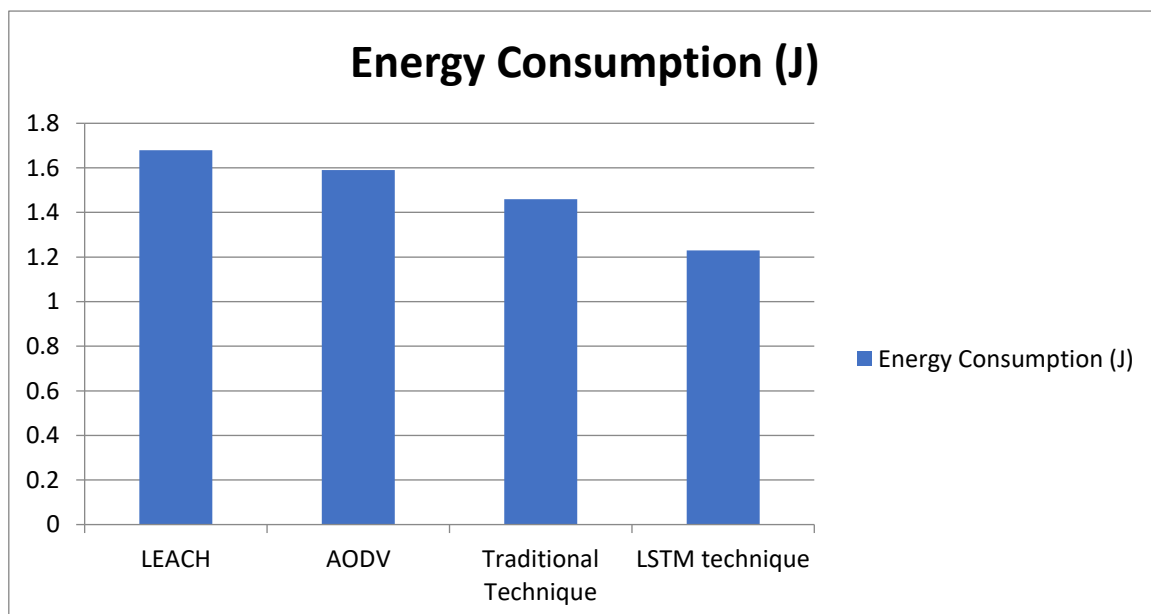


Figure 6: Graphical Energy Consumption (J)

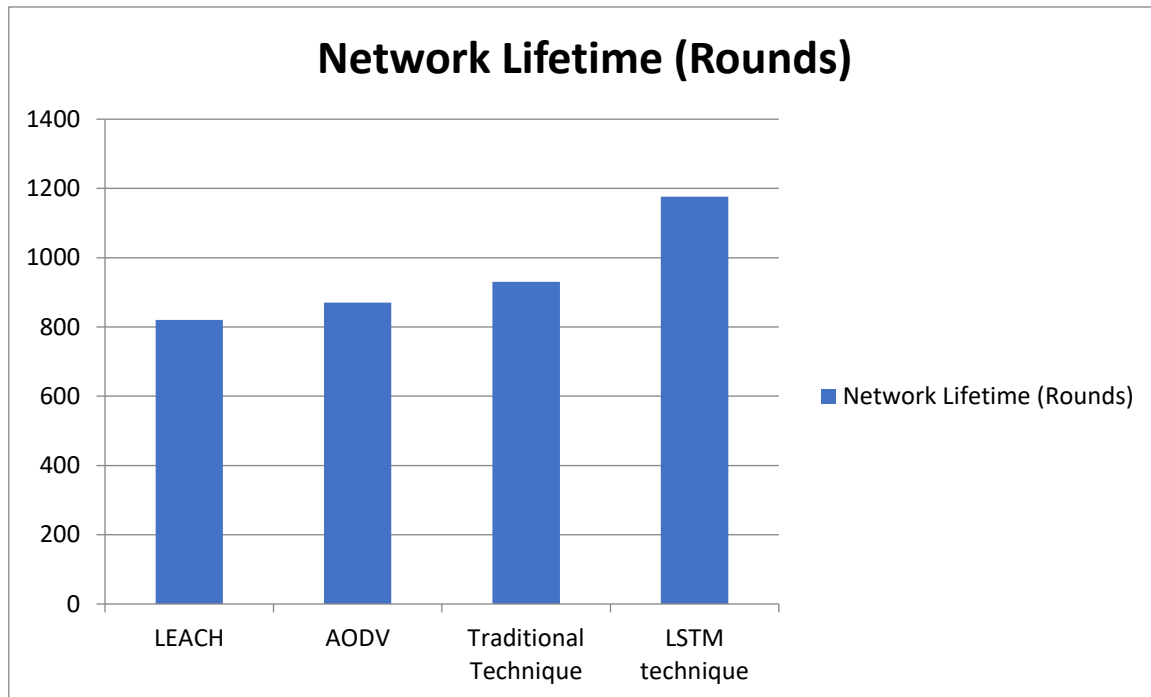


Figure 7: Graphical Network Lifetime (Rounds)

5. Conclusions

This paper presented an LSTM-based Predictive Congestion Aware Routing framework for enhancing energy efficiency and reliability in Wireless Sensor Networks (WSNs). Unlike traditional reactive congestion control mechanisms, the proposed approach leverages temporal learning capability of Long Short-Term Memory (LSTM) networks to forecast congestion conditions before they occur. By utilizing historical network parameters such as queue length, packet arrival rate, service rate, residual energy, and channel utilization, the model proactively predicts congestion probability and dynamically adjusts routing paths accordingly.

The integration of congestion prediction with an energy-aware routing cost function significantly improves overall network performance. Simulation analysis demonstrated high congestion prediction accuracy, along with strong precision and recall values, ensuring reliable detection of critical congestion events while minimizing false alarms. As a result, the proposed framework effectively reduces packet loss, decreases end-to-end delay, enhances throughput, and extends overall network lifetime. Load balancing across nodes further prevents hotspot formation near the sink and promotes uniform energy consumption.

Moreover, the adaptive learning capability of the LSTM model enables the system to respond efficiently to dynamic traffic variations and evolving network conditions. This makes the proposed scheme highly scalable and suitable for real time IoT applications, smart agriculture, environmental monitoring, healthcare systems, and mission-critical deployments.



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In conclusion, the LSTM-based predictive routing strategy provides a robust, intelligent, and energy efficient solution for congestion management in WSNs. Future work may focus on hybrid deep learning models, federated learning-based distributed training, and real-time hardware implementation to further enhance performance and scalability in large scale sensor networks.

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