Journal of Intelligent Systems and Internet of Things
Vol. 14, No. 02, PP. 08-24, 2025
DOI: https://doi.org/10.54216/JISIoT.140202

A New Adaptive-Clustered Routing Protocol for Indoor Fire Emergencies Using Hybrid CNN-BiLSTM Model: Development and Validation

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Abstract

This study presents a new adaptive routing protocol for fire emergencies, leveraging a newly created dataset and a hybrid deep learning approach to optimize decision-making and data routing strategies. The developed protocol integrates a hybrid of Convolutional Neural Networks (CNNs) with Bi-Directional Long Short-Term Memory (BiLSTMs) deep learning models to predict fires at early stages, effectively managing the dynamic and unpredictable nature of fire emergencies to prevent data loss and ensure packet delivery to the base station. Exhaustive validation was conducted utilizing the standard protocol to ensure the reliability and effectiveness of the proposed approach. Experimental results demonstrate the superior performance of the proposed hybrid-deep learning model and the significant enhancements in routing efficiency and monitored data preservation for the developed protocol compared to the standard protocol. The findings are useful in providing a reliable solution for adaptive routing during emergencies.

Received: March 06, 2024 Revised: June 12, 2024 Accepted: October 03, 2024

Keywords: Adaptive Routing Protocol; Hybrid Deep-Learning Model; Fire-Adaptive Dataset; Routing Failure; Network Segmentation; Data Loss

1. Introduction

Adaptive routing protocols in fire instances ensure reliable, effective, and prompt Wireless Sensor Network (WSN) communication. Such protocols manage the data routing, offering real-time monitoring and quick responses to changing conditions. They prolong the network's lifetime and ensure that vital information reaches emergency responders promptly by optimizing energy consumption and data transmission strategies. Adaptive routing approaches can adapt dynamically to the hazardous and unpredictable nature of fire progress, ensuring efficient communication. This adaptability is crucial for the effective management of incidents, enhancing situational awareness, and effective response during fire emergencies [1,2].

Numerous routing protocols were developed over time to solve a range of issues, including latency, fault tolerance, and energy efficiency. These protocols cover a variety of topics, from traditional algorithms created for general-purpose systems to more customized protocols developed for specific purposes like disaster recovery and emergency response in smart buildings [3,4]. The challenges in current routing protocols during fire incidents involved limited energy efficiency, poor real-time adaptation, and inadequate robustness in changing conditions. The struggle to handle these challenges leads to early node failure, network segmentations, and monitored data loss. Since fire accidents occur rapidly, protocols must be able to adapt dynamically to changing circumstances [5,6]. However, many protocols do not have the essential context awareness or real-time processing capabilities. These challenges highlight the need for advanced and adaptive protocols that can seamlessly incorporate environmental data and integrate predictive strategies to enhance the reliability and efficiency of routing protocols in fire incident emergencies and minimize data loss. More elaboration about current research gaps will be explained in the next section.

The main objective of this study is to develop a fire-adaptive routing protocol that ensures data delivery to Base Station (BS), handles network segmentation, and responds to rapidly changing infrastructure during indoor fire emergencies. The key contributions of this study are:

- Development of a new dataset for indoor fire emergencies based on sensor readings.
- Design a hybrid-deep learning model to be integrated within the standard routing protocol to make it adaptable to fires. Then, evaluate this model to assess its effectiveness with the new dataset.
- Validation of the developed protocol against standard protocol, utilizing metrics such as packet loss, packet loss ratio, and packet delivery ratio.

The rest of this paper is as follows: Section II elaborates on the literature review and highlights the research gaps. Section III describes the dataset used for this study. The hybrid deep learning model design and structure are explained in Section IV. Section V describes the development of the fire-adaptive routing protocol. The methodologies for hybrid deep learning model evaluation, the validation of adaptive routing protocol, and the simulation setup are explained in Section VI. Section VII displays and discusses the results of the proposed methodologies. Finally, the conclusion is highlighted in Section VIII. Table I lists the main acronyms and their definitions used in this paper.

Table 1: List of Main Acronyms with Definitions

Acronym	**Definition**
ACO	Ant Colony Optimization
AROA	Adaptive Remora Optimization Algorithm
BiLSTM	Bi-directional Long Short-Term Memory
BOA	Butterfly Optimization Algorithm
CNN	Convolution Nural Network
D3QN	dueling double deep Q-network
KNN	K-Nearest Neighbor
MFO	Moth Flame Optimization
PDR	Packet Delivery Ratio
PLR	Packet Loss Ratio

SFO	Sailfish Optimization
SHO	Spotted Hyena Optimization
SSO	Social Spider Optimization
SVM	Support Vector Machines
WOA	Whale Optimization Algorithm
WSN	Wireless Sensor Network
ZRP	Zone Routing Protocol

2. Literature Review

The development of routing protocols will be discussed in this literature, along with their prominent features, advantages, and limitations. The identified gaps from the literature review will be summarized, and the recent advancements that attempt to improve network performance under fire conditions will also be highlighted.

A dual-channel-based mobile ad hoc network (MANET) routing protocol optimized for indoor disaster environments has been developed [7]. The protocol utilizes both 2.4 GHz and sub-GHz channels to improve communication range and reliability. To optimize routing decisions, the method combines an indoor positioning system for accurate node localization with a unique routing cost computation based on signal-to-noise ratio (SNR) and node positions. To select the optimal Cluster Head (CH), Maheshwari et al. use the Butterfly Optimization Algorithm (BOA) and consider variables such as residual energy, node degree, node centrality, distance to neighbours, and the BS [8]. The optimal path between the CH and the BS is found using Ant Colony Optimization (ACO), which considers variables including node degree, residual energy, and distance. Metrics such as active nodes, dead nodes, power consumption, and received data packets by BS are included in the performance evaluation of the proposed approach. The outcomes are compared with those of more established techniques and more conventional strategies. Quoc et al. proposed a hybrid fault-tolerant routing for WSNs with a hierarchical topology that combines sensor node labelling with clustering as Gaussian integers [9]. A Gaussian network is created by connecting the small square grids that form the network area, each with a CH represented by a Gaussian integer. The proposed routing protocol was developed to improve WSNs' data dependability, fault tolerance, and energy efficiency. To improve the rapidity and reliability of crucial data transmission during emergencies, Tsai et al. provide an RPL-based emergency routing method for smart buildings [10]. The suggested protocol modifies RPL to improve routing paths depending on network conditions and prioritize emergency traffic. Compared to others, the protocol performs better when evaluated through simulations regarding packet delivery ratio, end-to-end latency, and energy efficiency. Mansour et al. introduce a novel Energy-Aware Fault-Tolerant Clustering with Routing for Improved Survivability (EAFTC-RIS) technique in WSN, attempting to select CHs and optimal routes using fault tolerance mechanisms [11]. The proposed protocol uses Moth Flame Optimization (MFO) for cluster formation and CH selection. The Social Spider Optimization (SSO) algorithm is also used for optimal route selection. By including clustering, routing, and fault-tolerant techniques with multiple input variables, the proposed protocol enhances network survivability, outperforming recent approaches. A predictive routing strategy for an indoor fire communication system was developed using mesh network technology [12]. Building fire emergency lights serve as mesh routers, while firefighter communicators serve as mesh terminals. By addressing the difficulties associated with indoor networks in intricate building construction, the system seeks to provide dependable fire emergency communication. To improve the indoor communication links' real-time dependability, the protocol switches the routing before the wireless communication links fail. In a work by Kaviarasan and Srinivasan, the multi-function formulation is derived using the Adaptive Remora Optimization Algorithm (AROA), which carries out the CH selection while considering variables such as distance, path loss, packet delivery ratio, energy consumption, and throughput [13]. The experimental result shows an extended network lifetime and reduces the energy consumption of the WSN routing protocol created using heuristics.

Yang et al. proposed a novel intelligent routing algorithm to address issues like short network lifetimes, high communication delays, and insufficient adaptability to changes in network topology [14]. The algorithm combines deep reinforcement learning for multi-hop path selection with swarm intelligence algorithms for CH selection. The protocol not only effectively decreases delay but also balances energy consumption and flexibly adapts to changes in network topology while determining the optimum multi-hop path, thereby extending the network's lifetime. Roberts et al. suggest an enhanced dual-phased paradigm for cluster-based, energy-efficient routing in wireless sensor networks [15]. It tackles the critical issue of striking a balance between energy usage and dependable network performance. Two sophisticated meta-heuristic algorithms, Sailfish Optimization (SFO) and Spotted Hyena Optimization (SHO), are included in the framework. SHO's sophisticated exploitation skills enhance effective routing paths, while SFO's rapid exploration is utilized for effective clustering and optimum CH selection. Ali et al. proposed routing protocol consumes less energy and extends the network's life compared with well-known protocols using fuzzy logic [16]. The proposed technique improves CH selection and multipath routing. It gains better performance under different numbers of nodes and different simulation times and enhances end-to-end time, energy consumption, packet loss rate, drop rate, and network resilience. Table II shows the analysis of the reviewed literature.

The research gaps could be identified by highlighting the issues that existing protocols face during fire incidents:

- Placement of BS within the network area makes it vulnerable to damage in indoor incidents, resulting in the entire monitored data loss during fire events.
- Not adaptive to environmental variations and dynamic scenarios, which caused network segmentation, routing failure, and infrastructure distortion. Reconfiguration mechanisms in dynamic environments are essential.
- Unexpected main node losses, such as CHs, forwarder nodes, relay nodes, and gateway nodes, were not considered. These nodes are often responsible for data aggregation and submission from sensor nodes to BS. The sudden loss of such nodes caused the loss of a large amount of data, if not all, based on the network architecture.
- Network heterogeneity should be considered to handle emergency scenarios. Heterogeneous networks ensure reliable, effective, and robust communication by utilizing the various capabilities of distinct nodes. This is essential for efficient emergency response and management during fire events.
- An adaptive dataset for indoor fire incidents does not exist. Developing a new fire-adaptive dataset for indoor routing protocols is critical for creating efficient, advanced, and reliable communication frameworks tailored to the complexity of indoor environment settings.

Therefore, it is important to develop an adaptive routing protocol for indoor fire incidents based on advanced artificial intelligence techniques and an adaptive fire dataset. This will provide robust, realistic, and accurate solutions for fire detection and response systems. These developments eventually result in the saving of lives and the reduction of property damage during fire disasters by improving safety, resource allocation, resilience, and interaction with smart building systems.

Table 2: Literature Review Analysis.

Study/ Year	Main Objective	Methodology	Strengths	Drawbacks	Network Segmentation/ Routing Failures Awareness
[7] 2020	Indoor disaster environment using MANET routing algorithm	Dual-Channel-based Mobile Ad-Hoc and Dijkstra's algorithm	Improved communication reliability Enhanced routing accuracy Faster network configuration	Node positioning inaccuracies may lead to suboptimal routing decisions Limited scalable protocol Sudden nodes' loss was not addressed	x
[8]	Reduce energy consumption and	Butterfly Optimization	Optimal CH selection	Limited scalability discussion	

2021	improve network lifetime for the proposed protocol	Algorithm (BOA) and Ant Colony Optimization (ACO)	Efficient routing Energy efficiency	Narrow comparison scenarios BS within the network area Sudden node loss was not addressed	x
[9] 2022	Develop a hybrid fault-tolerant routing solution for WSNs	Gaussian network	Reduced routing cost Energy efficient scheme	Packet delay BS within the network area Unexpected CH-loss was not considered	x
[10] 2022	Develop an emergency routing protocol for smart buildings	Emergency routing protocol based on IPv6	Reliability Low latency Energy efficiency Scalability	Isolated nodes and shortest paths are not addressed Focused on specific emergency scenarios Implementation complexity	x
[11] 2022	Optimal CHs and optimal routes selection with fault-tolerance mechanism	Moth Flame Optimization (MFO) and Social Spider Optimization (SSO)	Enhanced network survivability Efficient energy utilization Fault-tolerance mechanism Integrating advanced optimization techniques	Communication overhead Assumption of nodes' homogeneity BS location in the central network area Not adaptive to environmental variations and dynamic scenarios	x
[12] 2023	Enhance real-time and reliability for indoor communication links	Enhance the standard Zone Routing Protocol (ZRP)	Enhance packet delivery rate, throughput, and end-to-end delay Improve real-time communication links	Environment-specific model; limiting applicability Limited scalability Did not address data loss	x
[13] 2024	Develop an energy-efficient routing protocol	Adaptive Remora Optimization Algorithm (AROA)	Addressing energy consumption issue Solve the multi-function formulation issue within WSNs Efficient CH selection	Fault tolerance or adaptability to dynamic network conditions was not assigned BS location in the central network area	x
[14] 2024	To address issues like adaptivity, delay, and lifetime in traditional routing protocols	Whale Optimization Algorithm (WOA) and Dueling Double Deep Q-Network (D3QN)	Adaptability to environmental variations Eliminating hotspot problems Balance energy consumption Reduces communication delays	Computational complexity Obtaining accurate node locations might be a challenge Unexpected nodes' loss was not considered	x
[15] 2024	Provide energy-efficient CH routing	Sailfish Optimization (SFO) and Spotted Hyena Optimization (SHO)	Using a hybrid optimization strategy for efficient routing Balancing reliable data transmission with energy consumption Enhance lifetime and packet delivery	Not adaptive to environmental variations and dynamic scenarios BS inside the network area Framework scalability was not assigned	x
[16] 2024	Enhance CH selection and multi-path routing in WSNs	Fuzzy-Logic rule	Minimize energy consumption, end-to-end delay, and packet loss Enhance network resilience	Reconfiguration mechanisms in dynamic environments were not addressed Unexpected loss of head nodes such as CHs or relay nodes was not discussed	x

3. Dataset Description

It is critical to use a dataset for indoor fire incidents to design an adaptive routing protocol using a hybrid deep learning model. To our knowledge, no data has been developed for indoor fire incidents for an adaptive routing protocol. Therefore, this work uses a newly created dataset with the following configurations: The communication system is split into two main transmit functions: "transmit" and "receive." The data transmitter nodes are marked as level 1, and the data receiving nodes are marked as level 2. Level 1 nodes represent the normal sensor nodes, while level 2 sensors are the head nodes, cluster heads, or forwarder nodes. The fundamental assumption used for sensor nodes is that temperature and energy thresholds exist. If either the energy or temperature threshold fails to be satisfied, the sensor node is considered to have failed. The failed sensor node is brought back to life and allowed to rejoin the communication network after five cycles. The dataset has eight features:

- 'x_coord': The x-coordinate is a random value between 1 and 1000. If the sensor node is a level 1 node, this feature measures the x-coordinate from level 2 nodes, and vice versa.
- 'y_coord': The y-coordinate is a random value between 1 and 1000. If the sensor node is a level 1 node, this feature measures the y-coordinate from level 2 nodes, and vice versa.
- 'node_id': The node identity ranges from 1 to 300, with 250 for level 1 nodes and 50 for level 2 nodes.
- 'id_type': Identity type. Its value is 1 for level 1 nodes and 2 for level 2 nodes.
- 'energy': Node's current energy, even for level 1 or level 2 nodes. The value is randomized. For level 1 nodes, the energy value is between 500 and 1000. For level 2 nodes, the energy value is between 700 and 1000. Energy can indicate unusual patterns in fire-related incidents, such as rapid increases in power usage due to emergency reactions or equipment failures.
- 'temp': Node's current temperature, even for level 1 or level 2 nodes. The value is randomized. For level 1 nodes, the temperature value is between 20 and 40. For level 2 nodes, the temperature value is between 25 and 40. The real-time heat level is provided through the temperature feature, which may assist in the early detection and management of fires.
- 'status': 1 means the node is active; otherwise, the node is inactive. The active nodes have an energy value of ≥ 500 and a temperature value of ≤ 32. The inactive node could be burned or a failure node. The burned nodes have a temperature value of >32, and the failure nodes have an energy value of <500.
- 'priority': It is the last decision for a node and depends on the node's status in the next round. It refers to the node's transmission priority. The nodes nearest the failing temperature and energy thresholds, as well as the nodes nearest the level 2 nodes above them in the hierarchy, i.e., the BS, relay or forwarder node, and CH node, have the greatest node priority.

4. Hybrid Deep-Learning Model

Deep learning models must be utilized to create adaptive routing approaches, as they are effective at learning complicated patterns and providing real-time decisions using massive quantities of data [17]. Unlike traditional machine learning models such as decision trees, support vector machines (SVM), K-nearest neighbour (KNN), and logistic regression, deep learning provides dynamic adaptation to changing network situations, link quality prediction, and enhances routing paths with excellent accuracy [18,19]. This leads to routing systems that are more effective, reliable, and scalable and can manage the complexities and unpredictability of current communication settings, especially in critical instances such as response to emergencies and smart building management.

The dual-layer CNN-BiLSTM hybrid deep-learning model was selected as CNNs can excellently extract spatial features from data, such as patterns in signal strength and environmental layouts, which are essential in recognizing the indoor environment throughout a fire [20,21]. On the other hand, BiLSTM units are especially effective at capturing temporal sequences and dependencies, such as signal pattern changes in time, because of moving fire dynamics. They can incorporate past and future information to predict optimal routing decisions [22,23]. As a result, the CNN-BiLSTM model is an excellent choice for adaptive routing protocols in indoor fire incidents, considering its enhanced prediction accuracy, real-time adaptability, tolerance to environmental change, and superior feature extraction.

The layered structure for the proposed models is composed of two 1D convolution layers for the CNN model. The first layer has 16 filters and a filter size of 3, and the second layer has 32 filters and a filter size of 3. Each convolution layer is followed by the ReluLayer activation function, which is used to provide non-linearity and learn the complex mapping among input and output data. Two BiLSTM layers follow the convolution layers, each composed of 400 hidden units. The fully connected layer comes after the two BiLSTM layers; it incorporates the higher-level features extracted from the convolutional layers to provide the final output. The output of the fully connected layer reflects the classification derived from the learned features from the layers before it. The fully connected layer is followed by the SoftMax layer, which turns the model output into class probabilities. The number of input features in this model is 7, which excludes the priority feature as it will be the output class for this model. The CNN-BiLSTM model structure is shown in Fig. 1.

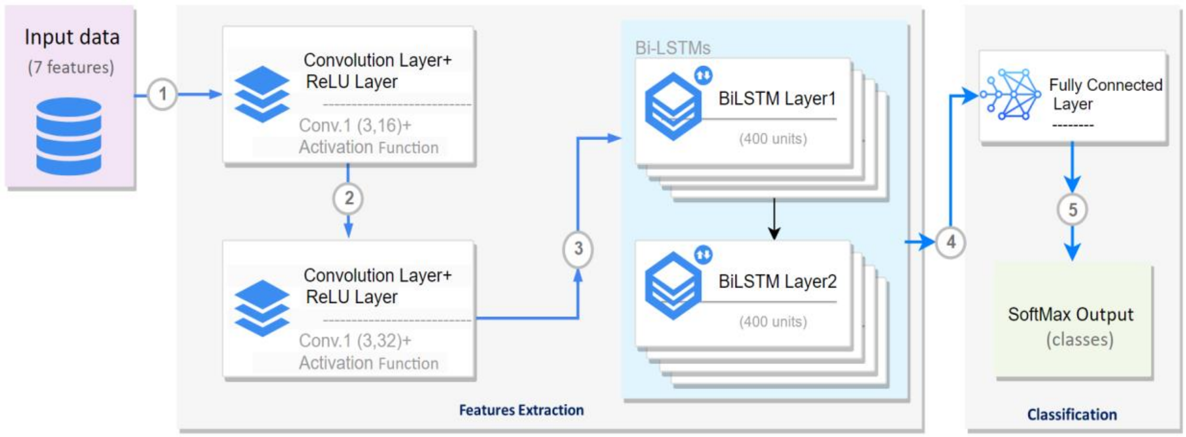

Figure 1. Layer Structure for the CNN-BiLSTM Hybrid Model

For the dual-layer CNN-BiLSTM model, the number of units in the sequence input dimensions is 7, the batch size is 1, the time-step dimension in various layers is 1, the number of filters in the first 1-D convolutional layer is 16, the kernel size of the convolutional layers is 3, the number of filters in the second 1-D convolutional layer is 32, and the number of units in each BiLSTM layer is 400 units, which is also the size of the hidden and cell states. Furthermore, the number of weights and biases in each BiLSTM layer, including the input weights, recurrent weights, and biases, is 1600. The number of units in the fully connected layer and the size of the activations in the softmax and classification output layers are 167. As a result, the total number of learnable parameters within this model is 140, 3287.

The normalization and preprocessing steps for training the CNN-BiLSTM model are as follows:

- Loading data and setting up a cell array for data storage
- Before processing, loop through each sheet, read the data, and make sure the sheet has data
- If there is an error reading or no data, set the cell to empty
- Remove empty cells from the array of data
- Dimensions definition; and reshaping the Excel data into a 3D array
- Input and output data preparation
- Virtualization of data after training
- Predictor model savings

5. Proposed Fire-Adaptive Routing Protocol

This study develops a new cluster-based fire-adaptive routing protocol for indoor incidents. The developed protocol is an optimized revision of the standard Energy Efficiency Multi-Stage Routing Protocol (EE-MRP) [24]. The network architecture of the developed protocol is split into three stages (S1, S2, and S3) based on the communication paradigm and five regions (S1, S2, S31, S32, and S33) based on the split regions, as shown in Fig. 2. Stage S1 is a cluster-based stage, where the CHs aggregate the data collected from the sensor nodes and then submit the data directly to the BS using single-hop communication. The stage S3, including S31, S32, and S33 regions, is also cluster-based. The CHs within S3 collect and aggregate the data from the corresponding sensor nodes, which are then submitted to a central node placed in S2 called the Forwarder Node (FN). Stage S2 is not a cluster-based stage, and the sensor nodes within S2 submit the data to the FN, which aggregates the collected data from S3 and S2 and then submits it to the BS using multi-hop communication. With this communication mode, the energy consumption will be balanced among all regions' nodes based on the hop count strategy and the distance to the BS. Fig. 3 shows the data routing flowchart for the developed protocol.

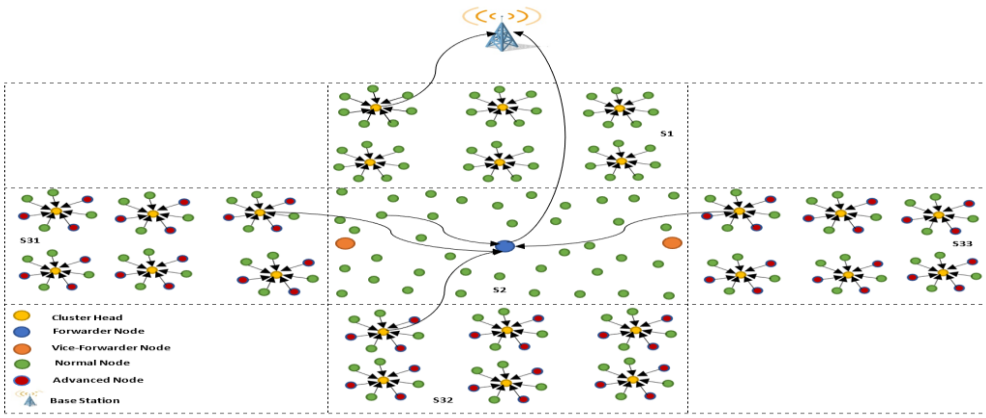

Figure 2. Communication Model for the Proposed Protocol.

The following network assumptions were considered for developing the fire adaptive routing protocol:

- BS is located outside the network area to protect it from loss due to indoor fire incidents.
- The FN is a robust battery-dependent node that can be replaced or recharged.
- Two vice-FNs are placed on the right and left sides of S2. It has the same specifications as the main FN and remains in sleep mode unless the algorithm predicts the main FN damage due to fires. Then, the algorithm sends the wake-up message and selects the vice-FN with the low temperature to take responsibility.
- Sensor nodes within regions are energy-constraint nodes and cannot be recharged.
- Nodes within S1 are homogeneous, where all nodes have identical initial energy and no need for heterogeneity due to their location within the vicinity of the BS. Further, nodes within S2 are also homogenous, as their function is just to monitor data within S2 and then submit it to the FN. It will not exhaust further energy to submit the data to faraway nodes.
- Nodes within S3 are heterogeneous. Because the two vice-FNs are situated on both ends of S2, some CHs in S3 require longer transmission times than others to send data to the vice-FN during a fire event. Furthermore, all CHs in S3 will transfer the data directly to the BS if both vice-FNs are burned. Hence, more energy is required for data transmission during the fire because of the longer distance between CHs in S3 and BS, or vice-FNs.
- All sensor nodes within the network infrastructure incorporate built-in temperature sensors for instantaneous measurement.

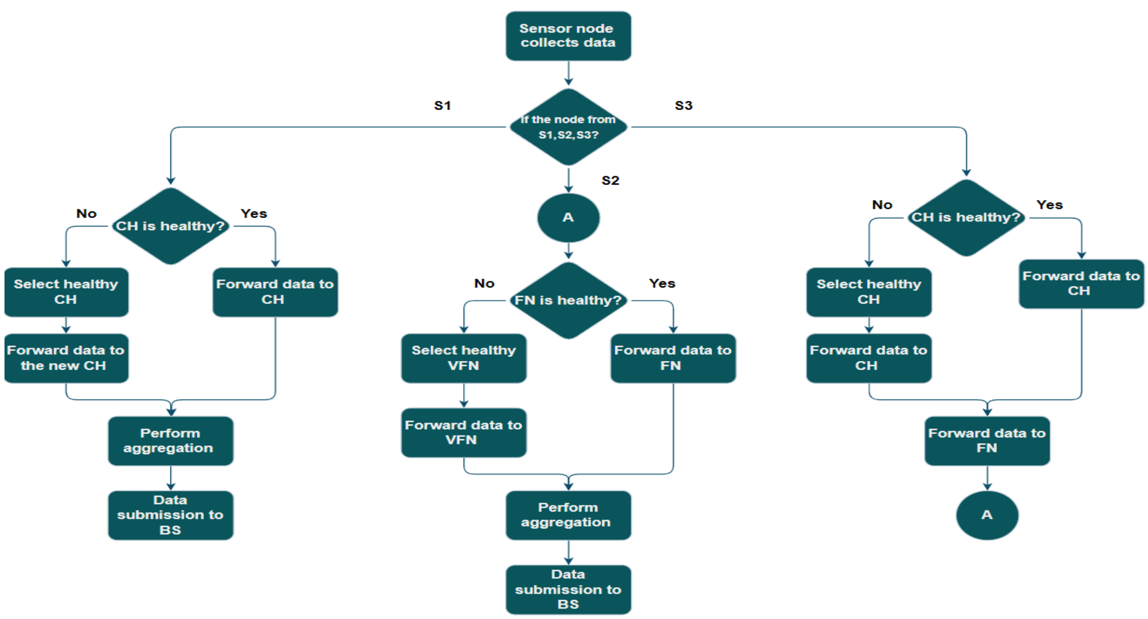

Figure 3. Data Routing Flowchart for the Developed Protocol

The CH replacement was based on a threshold level in the standard protocol. For the developed protocol, the CNN-BiLSTM model was incorporated into the adaptive protocol and trained with the created dataset to be used in the CHs replacement process. Three aspects are considered for CH replacement: temperature, energy, and distance. In a fire event, the burned CH is replaced by a healthy node. To ensure that it is not burned by the fire that destroyed earlier CH, high residual energy, low temperature, and significant distance from the burned CH are critical considerations. Fig. 4 elaborates on the CH replacement strategy within the adaptive routing protocol.

The standard routing protocol offers no alternative to the main FN in the event of failure. Any node in the network domain cannot substitute the FN due to its unique features, including battery power dependency, replacement and recharging capabilities, and handling of S2 and S3's data aggregation and submission. Consequently, the FN in the adaptive protocol has two vice-FNs aligned on S2's left and right sides, and the hybrid deep-learning model manages the FN replacement process. When data is submitted from S2 or S3 to the FN, the algorithm checks the status of the FN. If the FN is active with a temperature value below the threshold value, then the data will be submitted to the FN, and the FN will submit the data to the BS. If the FN temperature reaches the threshold temperature level, the algorithm sends a wake-up message to the two backup nodes. The responsibility of the FN will be forwarded to the backup FN that has the lower temperature value, and the algorithm will broadcast a message to all stages to inform them about the new FN. The other vice-FN will go to sleep, and the new FN will take on the responsibility of data aggregation and submission to the BS until the central FN is back to life again.

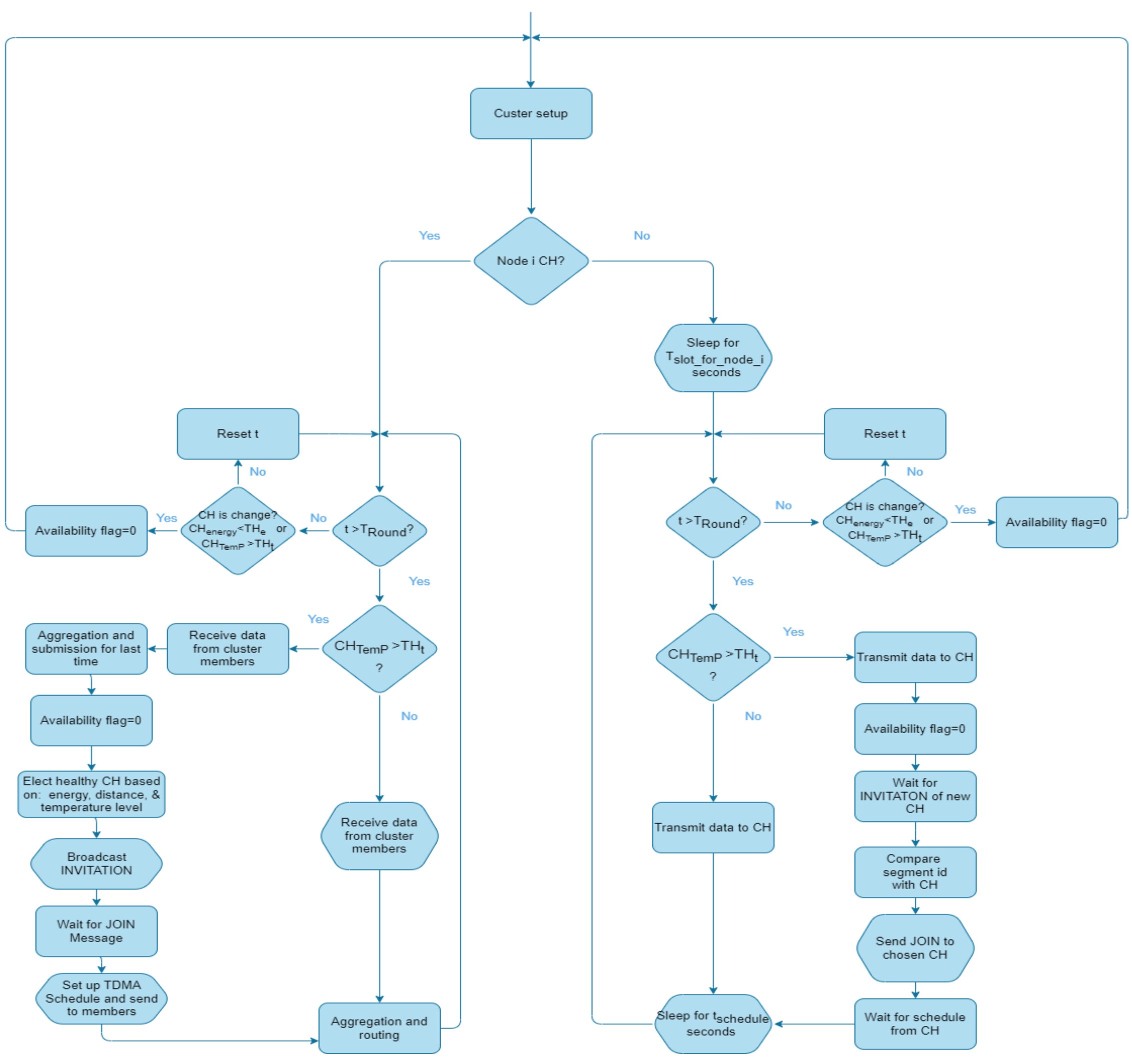

Figure 4. The CH Replacement Flowchart of the Developed Protocol

6. Evaluation and Validation Methodologies

This section discusses the evaluation of the selected CNN-BiLSTM model, and the validation of the proposed fire-adaptive routing protocol compared to the standard routing protocol. The experimental setup will be discussed further in this section.

A. CNN-BiLSTM Evaluation

The evaluation criteria are essential for deep learning model evaluation as they verify the model's effectiveness, relevance, and equity. It measures the completeness, accuracy, and reliability of the used dataset and offers a standardized method to measure the model's performance in terms of prediction and classification. Four evaluation criteria will be used to evaluate the hybrid dual-layer CNN-BiLSTM model: accuracy, precision, recall, and F1 score. The accuracy is the ratio of correct predictions to the total predictions, as shown in Equation 1. Precision is the ratio between correct and total positive predictions, as shown in Equation 2. The recall is the ratio between correct positive predictions and all positive labels, as explained in Equation 3. The F1 score is a harmonic relationship between precision and recall, as shown in Equation 4. For all equations, the predictions derived from dataset evaluation are divided into four categories: False Positives (FP), True Negatives (TN), True Positives (TP), and False Negatives (FN).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1 score} = \frac{TP}{TP+\frac{1}{2}(FP+FN)} \quad (4)$$

The loss function, LF is another metric for evaluating the proposed deep learning model. It is the difference between the predictions and the actual values. MATLAB incorporates various built-in loss functions; however, the cross-entropy loss function LF is utilized for multi-class classification, as shown in Equation 5:

$$LF = -\frac{1}{m}\sum_{i=1}^{m}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c}) \quad (5)$$

Where, C is the class number, m is the iteration number, $y_{i,c}$ is a binary indicator (0 or 1) if the class target C is the correct classification for the observation i, and $\hat{y}_{i,c}$ is the probability predicted from the observation i in class C.

B. Adaptive Routing Protocol Validation

The developed protocol was validated utilizing the same fire scenario for both fire-adaptive and standard protocols. The Packet Loss Ratio (PLR) and Packet Delivery Ratio (PDR) in the fire scenario for both protocols were compared to determine performance. The developed protocol must have a significantly lower PLR and higher PDR than the standard one, and it must function better during fires. This is a result of the embedded hybrid deep-learning model in the developed protocol to increase its adaptivity to handle fire incidents.

The PLR and PDR were measured by computing the total transmitted packets and total received packets after the fire. In Equation 6, the total transmitted packets to BS for all regions, T_{TP} is equal to the sum of the total packets transmitted for each region, TP_{Pk}, where K is the region's number from 1 to 5:

$$T_{TP} = \sum_{1}^{K} TP_{Pk} \quad (6)$$

The total loss T_L is equal to the sum of packet losses in all regions:

$$T_L = \sum_{1}^{K} PL_K \quad (7)$$

where PL_K is the packet loss for the region K; and it is equal to the sum of the dead nodes for the region K .$\text{Dead}_{\text{nodes}_K}$, multiplied by the number of the acquired packets for each dead node, $NAP_d^{(k)}$; as shown in Equation 8, where d is the dead node:

$$PL_K = \sum_{d=1}^{\mathrm{Dead}_{\mathrm{nodes}_K}} NAP_d^{(k)} \quad (8)$$

The total number of received packets after the fire TR_{AF} is equal to the difference between the total transmitted packets T_{TP} and the total loss after the fire T_L, as explained in Equation 9:

$$TR_{AF} = T_{TP} - T_L \quad (9)$$

Now, the PLR is measured by the ratio between the total loss after the fire T_L and the total transmitted packets T_{TP}; as shown in Equation 10:

$$PLR = \left(\frac{T_L}{T_{TP}}\right) \times 100\% \quad (10)$$

Finally, the PDR could be measured as the ratio between the total packets received at the BS after the fire TR_{AF} to the total transmitted packets T_{TP}, as shown in Equation 11:

$$PDR = \left(\frac{TR_{AF}}{T_{TP}}\right) \times 100\% \quad (11)$$

C. Simulation Setup

For this study, the dataset creation, deep-learning model design and evaluation, and adaptive protocol development and validation were all conducted using MATLAB 2023b.

One of the most significant simulation setup procedures is hyperparameter tuning. Evaluating the performance of the trained hybrid deep-learning approach is essential, usually set before the training process. The frequently utilized hyperparameters are the epochs, learning rate, minibatch size, optimizer, activation functions, and number of hidden units. As a lower learning rate typically results in more stable training, we set the learning rate to 0.001. The learning rate drop factor was set to 0.1.

The epoch is a single, complete cycle. It was set at 3,000. The data sample number utilized in each training cycle is defined by the minibatch size, which is set at 64. Depending on the minibatch size and epoch number, an automated adjustment is made to the number of iterations per epoch. Adam is an optimization technique that adjusts the parameter's learning rate to improve the performance and speed of neural network training. The dataset splitting ratio was set to 80/20, with 80% for training sets and 20% for testing sets. The number of hidden units is 200, but in the BiLSTM model, which achieves bi-directional training in the past and future, the hidden unit is 400 for each BiLSTM layer. The network parameters for the developed protocol were adjusted as shown in Table III.

Table 3: Network Parameters Adjustment.

Parameters	Value
Network Rigon	(300x150) ft2
Sensor nodes per region “For S1, S3, S4, S5”	94
CHs per region “For S1, S31, S32, S33”	6
Sensor nodes for S2 Including FN	95
Total nodes for all regions “including FN”	495
FN location	150x75
Left vice-FN location	105x75
Right vice-FN location	195x75
BS location	150x200
ETX “Transmission energy”	50nJ
ERX “Reception energy”	50nJ

*E*amp “cluster to BS/FN energy”	0.0013 pJ/bit/m4
Efs “cluster to BS/FN energy”	10 pJ/bit/m2
*E*da “Energy consumed for data aggregation”	5nJ/bit
Eo “Initial energy for sensor nodes”	0.5J
Eoc “Initial energy for CHs”	1J
K “Number of regions”	1-5
Packet size	50kb

7. Results and Discussion

This study divides its results into two parts: the evaluation of the deep learning model and the validation of the developed routing protocol, as detailed below:

A. CNN-BiLSTM Evaluation

Utilizing the created dataset, the CNN-BiLSTM model is trained to evaluate the effectiveness of the dataset. The hyperparameters are set to 3000 for the maximum epoch, 64 for the minibatch size, 4 for the number of iterations per epoch, and 12000 for the maximum iterations, which is equal to the number of epochs multiplied by the number of iterations per epoch. 0.001 was selected for the learning rate as well as the Adam optimizer. To evaluate its performance, the CNN-BiLSTM model was compared to the CNN and LSTM models. The CNN model is composed of a 1D-convolution layer with 16 filters with 3 filter sizes, followed by a Relu activation function, a fully connected layer, and a Softmax classification output. The LSTM model is composed of one LSTM layer of 200 units, followed by a fully connected layer and a Softmax classification output.

Table IV and Fig. 5 show the evaluation metrics for the deep learning models. The CNN model is ineffective at handling sequential data and is typically used to extract special features from image data. Therefore, it records low evaluation metrics, with an accuracy of 74.08%, precision of 78.33%, recall of 77.01%, and F1 score of 77.67%. In addition, it records a high loss value equal to 1.0237. The LSTM model can efficiently handle sequential data, such as sensor data, and extract temporal dependencies. As a result, this model outperformed the CNN model. It records efficient evaluation metrics, with an accuracy of 93.67%, precision of 91.55%, recall of 92.15%, and F1 score of 91.85%. Moreover, a lower loss value of 0.2255 is recorded.

The CNN-BiLSTM model records high performance during the training of a sensor data dataset since it effectively integrates the strengths of CNNs and BiLSTMs. The CNN layers are perfect for extracting spatial features and capturing essential patterns from the sensor data. The BiLSTM units are adept at managing temporal sequences, ensuring that they learn from long-term dependencies within the data. This synergy enables the model to create accurate predictions, resulting in high-performance metrics during training such as low loss and high accuracy during training. Therefore, the model records 100% value for the accuracy, precision, recall, and F1 score metrics, as well as a very lower loss equal to 0.0003. As a result, the dual-layer CNN-BiLSTM model will be an effective model to be integrated into the protocol to acquire adaptability during fire incidents by preventing data loss. The training time for the CNN-BiLSTM model is equal to 66.51 minutes. It is longer than CNN and LSTM models due to the multi-layer structure, which increases computational complexity. In addition, BiLSTMs handle the data sequentially in a bi-directional way. The LSTM recorded 21.39 minutes of training time. It also handles the data sequentially, but it has a simpler layer structure than the CNN-BiLSTM model. However, the CNN model recorded a lower training time, equal to 12.28 minutes, due to the simple layer structure and parallel data-processing nature.

Table 4: The Performance Evaluation Metrics for the Evaluated Models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Loss Function	Training Time (Minutes)
CNN	74.08	78.33	77.01	77.67	1.0237	12:28
LSTM	93.67	91.55	92.15	91.85	0.2255	21:39
CNN-BiLSTM	100	100	100	100	0.0003	66:51

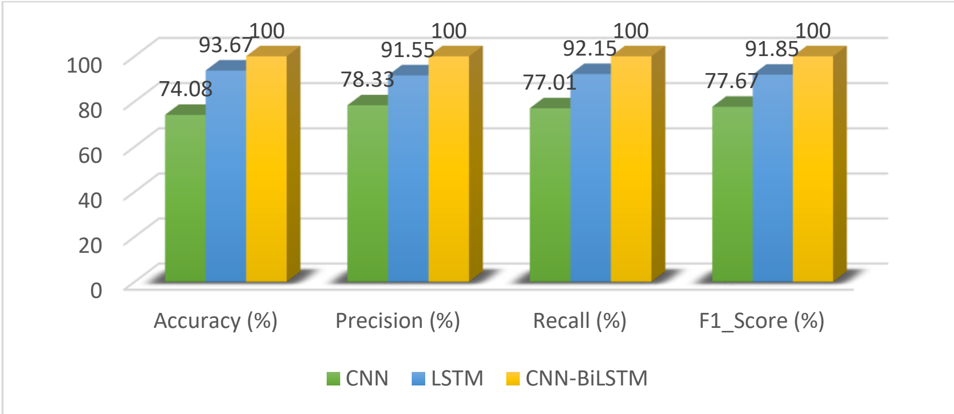

Figure 5. The Evaluation Metrics for the Comparative Models

B. Fire-Adaptive Routing Protocol Validation

Utilizing the fire scenarios, the fire-adaptive routing protocol can be validated against the standard protocol. Every node in the standard protocol has the same energy, and the algorithm lacks a classifier and backup forwarder nodes. Furthermore, as the fire spreads, nodes continue to burn, and data continues to be lost as the routing algorithm is not fire-adaptive. By integrating the CNN-BiLSTM deep learning approach into the proposed fire-adaptive routing protocol, the algorithm can adapt to fire incidents. The developed algorithm forecasts the fire in response to the temperature gradient measurement for the CHs or FN. If the temperature reaches critical values, the node transmits its collected data and transfers the responsibilities to an effective alternative node, depending on predefined criteria. The replacement criteria for the burned CHs are the greatest distance to the burned CH, the lowest temperature level, and efficient energy. On the other hand, the lowest temperature value is the parameter for the FN replacement. The adaptive routing protocol validation could be achieved by the three following scenarios:

- **Ideal Scenario (Without Fire)**

In the ideal scenario, the standard and developed protocols are in normal condition. It is assumed that every node has a good energy value and operates in an ideal condition where it can function until its energy runs out. Fig. 6 depicts the standard and adaptive protocol behavior within ideal conditions: all sensor nodes can detect the area, and head nodes can collect, aggregate, and submit the data to BS seamlessly. Table V shows the validation criteria for both protocols in the ideal scenario. At the BS, all submitted data was successfully received. The total number of transmitted packets is 23,500, resulting from the 50 kb packet submitted by each of the 470 sensor nodes. 25 head nodes are located within the area, where six CHs exist in each of S1, S31, S32, and S33, and one FN exists in S2. This data was received without loss at the BS. As a result, there is 100% PDR, zero PLR, and no packet loss.

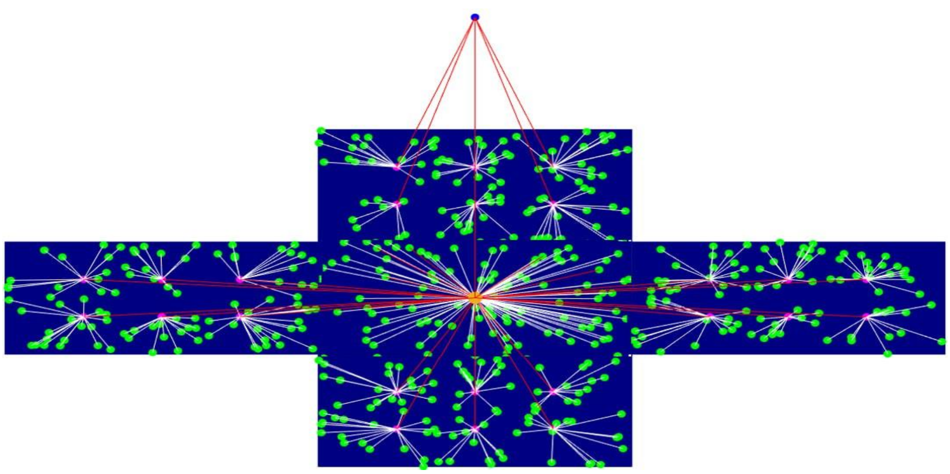

Figure 6. Ideal Scenario (Without Fire) for the Standard and Fir-Adaptive Protocols.

Table 5: The Outcomes for the Ideal Scenario (Without Fire).

Routing Protocol	Packet Loss (Packets)	PLR%	PDR%
Standard Protocol	0	0	100
Fire-Adaptive Protocol	0	0	100

- **Fire Scenario#1**

Only stage S1 has a fire in this scenario. The algorithm in the standard protocol remains sensing and submitting the data to the BS with the increased temperatures and loss of nodes and data, as shown in Fig. 7. Table VI. explains the validation metrics for the standard and developed protocols. In the standard protocol, the CHs in S1 cross the temperature thresholds without realizing their burning. They keep collecting data from the corresponding cluster until they die and lose the monitored data. Therefore, the packet loss is 1850 packets, PLR is 7.87%, and PDR is 92.12%.

The developed protocol behaviour for this scenario is shown in Fig. 8. It records a packet loss of 1100 packets, a PLR of 4.68%, and a PDR of 95.31%. The adaptive algorithm enhanced the developed protocol's adaptivity against fires, resulting in a lower PLR and a higher PDR. If the CHs predict the burn, they will submit the data to the BS one last time, switch to sleep mode, and then forward their responsibility to an active CH. This strategy ensures that data reaches the BS as well as reduces data loss in S1. As a result, the evaluation metrics show that the developed protocol outperforms the standard in terms of effectiveness during fires in this scenario. However, the enhancements in the values of PLR and PDR in the developed protocol are slight compared to the standard protocol because the fires are exposed only to one region of the network area.

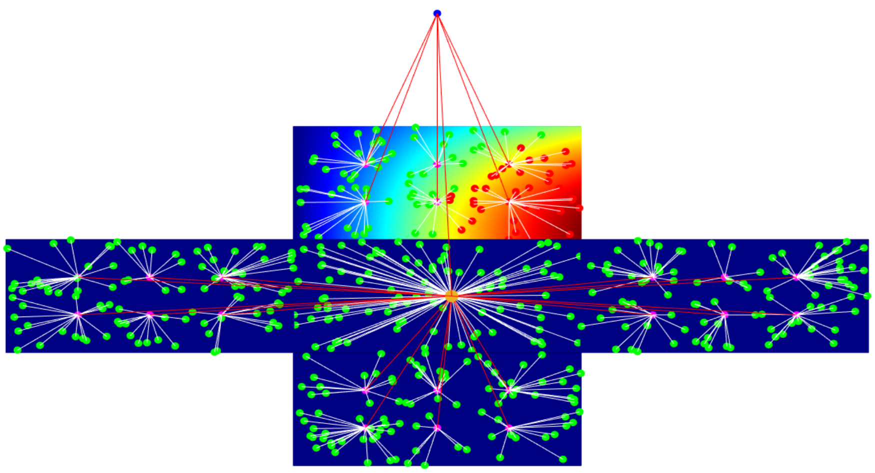

Figure 7. The Fire Scenario#1 for the Standard Protocol

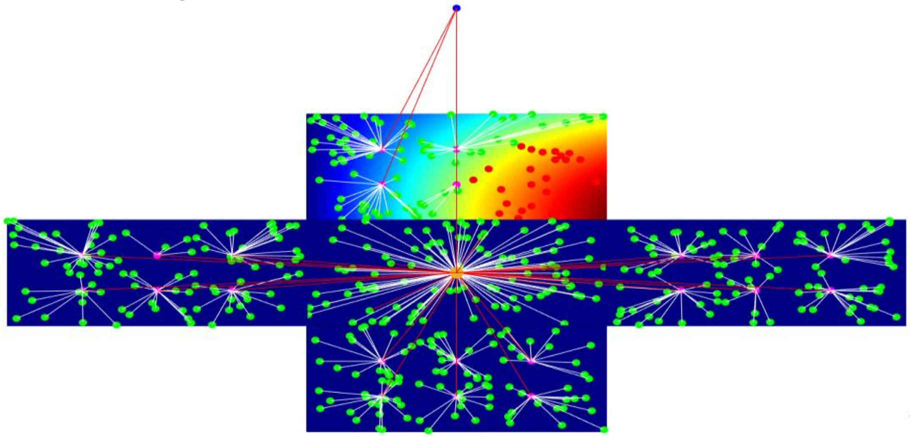

Figure 8. The Fire Scenario#1 for the Fire-Adaptive Protocol

Table 6: The Outcomes of the Fire Scenario#1.

Routing Protocol	Packet Loss (Packets)	PLR%	PDR%
Standard Protocol	1850	7.87	92.12
Fire-Adaptive Protocol	1100	4.68	95.31

- **Fire Scenario#2**

In this scenario, fires started in all stages of the network area and moved in various directions. It is the worst-case scenario, as more than 50% of the network area is fire-affected. Fig. 9 depicts the algorithmic behavior of the standard protocol. In contrast, the developed protocol behavior is shown in Fig. 10. Table VII illustrates that the packet loss in the standard protocol is 20150 packets, while the total number of received packets at the BS is 3350. Therefore, the PLR is 85.74% and the PDR is only 14.2%. In this scenario, the standard protocol recorded an extremely significant packet loss. This is expected since there is no adaptive mechanism to mitigate damage caused by fire. In addition, over 50% of the network has been burned, including the FN, which oversees 80% of the data collection and submission to the BS. For the developed protocol, the packet loss is only 9100; hence, the PLR is 38.72% and the PDR is 61.27%. Even though it is a worst-case scenario, where all regions have fires, the fire-adaptive protocol delivered 61.27% of sensing data to the BS. However, the standard protocol could deliver only 14.2% of the data to the BS, rendering the protocol approximately useless. The validation summary for both the developed and standard protocols is presented in Fig. 11. It shows the effectiveness of the proposed protocol during a fire in terms of preserving monitored data and managing data loss in a fire situation.

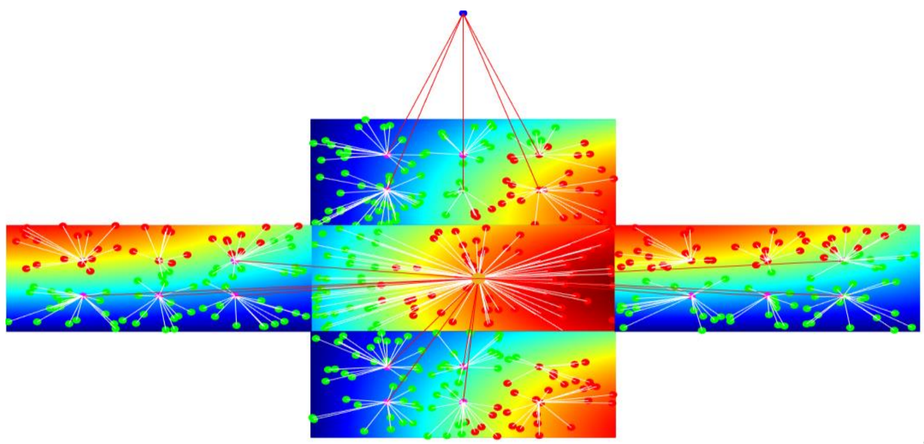

Figure 9. The Fire Scenario#2 for the Standard Protocol

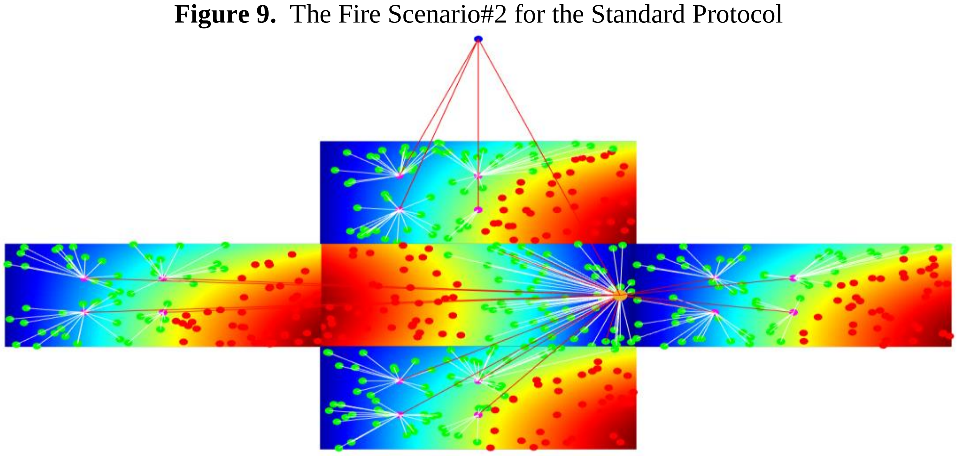

Figure 10. The Fire Scenario#2 for the Fire-Adaptive Protocol

Table 7: The Outcomes of the Fire Scenario#2.

Routing Protocol	Packet Loss (Packets)	PLR%	PDR%
Standard Protocol	20150	85.74	14.2
Fire-Adaptive Protocol	9100	38.72	61.27

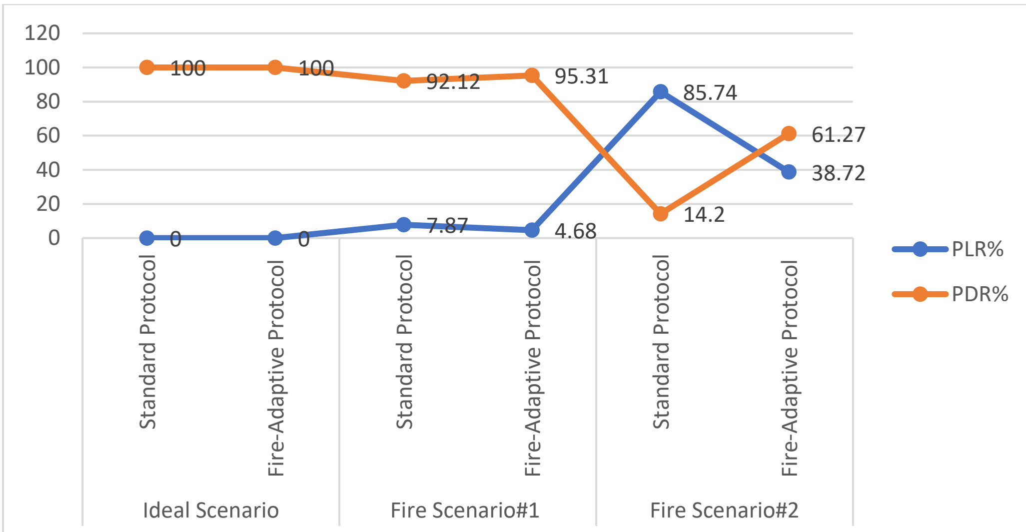

Figure 11. Validation Summary for Both Protocols.

8. Conclusion

This study investigates a new fire-adaptive routing protocol for indoor environments. A new dataset has been created to meet the unique requirements of indoor fire emergencies. The dual-layer CNN-BiLSTM model was integrated into the standard protocol to gain fire-adaptivity. The models recorded 100% accuracy, precision, recall, and F1 score metrics. In addition, the model records a low-loss function equal to 0.0003. The developed routing approach was validated with the standard protocol in a fire scenario. 50% of the network area had been set ablaze. The developed protocol was able to deliver 61.27% of the data to BS with only 38.72% loss. In comparison, the standard protocol lost 85.74% of the data and could deliver only 14.2% of the data to BS, rendering the protocol roughly useless. The developed protocol ensures its robustness and effective communication during indoor fire emergencies. However, the developed protocol suffers from redundancy in energy and data during fire incidents due to its multi-decision nature. In the future, we intend to handle these redundancies using a redundancy-aware mechanism.

Funding: “This research received no external funding”

Conflicts of Interest: “The authors declare no conflict of interest.”

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