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An efficient disaster management system based on deep learning in bio-inspired wireless sensor network

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Abstract

The risk rates, such as death, injuries, and distress, are increased in natural and artificial disasters. So, timely control and management of such disasters is a necessary process. The Wireless Sensor Network (WSN) plays a vital role in this process. However, in such techniques, prediction and communication sometimes fail. Therefore, a novel Jellyfish-based Deep Neural Disaster Management (JbDNDM) framework was developed for disaster management phenomena to address these limitations. Initially, the required nodes and network are initialized in the monitoring regions. The proposed JbDNDM system is activated at the sensing module of the network to sense the building fire and the affected zone based on parameters such as smoke, temperature, and gas mixture using the fitness function of the jellyfish and estimating the affected people. The sensed information is then sent to the management to provide emergency favors. Furthermore, the proposed JbDNDM approach was implemented in the MATLAB tool with several performance measurements such as delay, throughput, network lifetime, sensing accuracy, and Packet Delivery Ratio (PDR). The utilization of multi-relay communication increased the network performance, and the jellyfish function increased the sensing accuracy. The network efficiency results were compared with the existing techniques, such as OECF, HMRN, and WWO. The Proposed network obtained 0.01ms delay, 80.01Kbps throughput, 99.7% PDR, and 75h network lifetime. The sensing accuracy of the model is 99%.

Keywords: Disaster management, Deep neural network, Wireless sensor network, Jellyfish optimization, Sensing parameters

1. Introduction

In recent decades, WSN has been utilized as an emerging field of research for extensive progress in real-time disaster management. A Sensor Network (SN) could be built by merging identical or varied sensors [1]. In WSN, the biological data was sensed through a different set of independent sensors, and this data was sent to important regions via the network. SN motivated and developed several applications, such as health monitoring via body area networks, device status monitoring, and civil and disaster management [2, 3]. These types of networks could be used to supervise and analyze the storm/tornado movement, monitoring the warmth of the surrounding volcano and the behavior of the wild animals [4, 5]. The sensor nodes provide a way to communicate the sender to the receiver. Limited resources were used to make this path. The WSN performance was affected by several factors, such as bandwidth, scalability, power consumption, mobility, and data aggregation [6, 7]. Due to limited power sources of nodes, reducing power consumption was the essential problem in WSN [8]. During the communication phenomena, maximum energy is consumed through sensor nodes. Routing algorithms must be robust and straightforward to ensure less energy consumption. Due to the WSN's limited node resources, the node's lifetime was extended through the routing protocols [9, 10].

Disaster management is widely adopted with four stages: mitigation, preparedness, response, and recovery. Relief could prevent disaster occurrence or diminish disaster impacts [11]. Preparedness includes the community actions in terms of disaster, formed with an emergency plan, supply prepositioning, training, and education to the community to respond when striking disaster or mitigating the disaster effect [12, 13]. The response included implementing the plan for protecting the people's lives and property, the structure of a socio-economic community, and environmental strategy. Disaster relief and response include executing emergency planning, rescue, medical care, supply distribution, and damage assessment [14, 15]. Recovery had the long-term performance of financial assistance and rebuilding or reconstruction. In these phases, time was essential for disaster management. Disasters, such as earthquakes and floods, generate an emergency situation. Due to the escalation of catastrophe, a warning and remote control system must be designed [16, 17].

The primary complex task in disaster management was error tolerance. There was a sudden rise in present disruption from the sensing system based on dynamic paging, software, and hardware problems such as minimum power signal or storage space hardening should be higher for constructing the flawless phenomena and fault tolerable aspect of the process [18, 19]. Building fires are a leading

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cause of fire-related deaths, with an estimated 340,000 fatalities worldwide each year. The rapid spread of fire, coupled with the potential for smoke inhalation, poses a severe risk to occupants. It causes substantial property damage, destroying structures, equipment, and personal belongings. The financial losses can be devastating for individuals and businesses. Building fire disasters pose a significant threat to life and property, causing immense damage and loss. These fires can rapidly spread through buildings, trapping occupants and hindering firefighting efforts. The consequences of building fires are far-reaching, impacting individuals, communities, and economies. Traditional fire detection systems often rely on smoke detectors, which may not activate until the smoke has already accumulated, posing a delay in alerting occupants and firefighters. WSNs are susceptible to factors such as signal interference, battery depletion, and sensor malfunctions, which can compromise their reliability and accuracy in detecting and alerting fire hazards. The large volume of data generated by WSNs requires efficient data management and analysis techniques to extract meaningful information and trigger timely responses due to imperfections in the background of a network crash, including the drained battery, errors in quantity, and fault conditions produced in the communication defeat [20]. Then, another challenge was standardization, defined as the multiple forms of catastrophes in which various solutions were essential to defend against the standardization process. The high investment cost and human negligence were crucial challenges in disaster management [21]. A novel Jellyfish-based Deep Neural Disaster Management (JbDNDM) framework was developed for disaster management phenomena to overcome these problems.

The studied research article was arranged as follows: recent literature works were explained in section 2, and system design with problems was discussed in section 3. Consequently, the novel designed scheme was elaborated in section 4, and outcomes and comparison assessment were detailed in section 5. Finally, the research discussion was concluded in section 6.

2. Related work

Several recent works of literature based on the Disaster Management System were described as follows:

An energy effectiveness and service quality grouping was used with the support of biological routing procedures for efficient data transmission and emergency supervision of disaster via sensing nodes at the network. Therefore, Wilson and Radhamani [22] proposed the optimized ensemble clustering technique using the Black Widow algorithm to collect and transmit the data for emergency disaster management. This unified, scalable clustering process has two stages: ensemble generation and consensus function. The first stage engaged a diverse set, and the clustering was high quality. The next step involved combining multi-base clustering into robust consensus clustering. Then, self-configuration and self-organization problems were solved using the black widow optimizer, which regained the selection of route technique that recompenses the energy level of node and communication link quality. Finally, the method was implemented in a MATLAB simulator. However, the network cost should be practical and needs to diminish the node's delay characteristics.

Liu et al. [23] suggested a TORA routing protocol for the flood control process. Initially, transform the self-repair process in the graphical method into the optimized search nodes. Next, that node was searched based on the Ray algorithm. Then, validate the self-repair function for initiating the threshold. Also, the mapping process was done among the self-repairing nodes, space among the nodes was generated, and the path rebuilding was approved before the failure. Finally, control overhead was diminished, and the percentage of self-repairing routed efficacy was enhanced by determining the optimization region. Hence, the end-to-end delay still needs to improve the performance and provide the mapping relation between the network environment and flooding characteristics.

Natural disasters are determined as a lot of natural disasters and risks. Every year, human-made disasters bring about architectural defects, revenue loss, distress, and injuries due to higher death rates. So, Anbarasan et al. [24] discussed the Convolutional network that aimed to detect flood disasters. Initially, get the input data. Then, HDFS map-reduce was utilized to minimize the repetitive data. Then, the data was pre-processed after the repeated data was removed using the normalization and missing value imputation function. Next, pre-processed data was centered, and the rule was produced using a combined process of attributes technique. Finally, the input provided for the generated rules to network classifier into two chances: chances for flood and no chances of the flood occurring. This system needs to decrease the cost of the sensors for the flood detection process.

The distant observation of crucial disaster or hazard detection incidents in huge areas was a vital task. Then, incidents that occur in the monitoring environment cause stress on the normal execution of the system. So, Lino et al. [25] presented the Cluster Tree Reconfiguration technique that helped assign communication resources to the overloaded tree branches depending on the generated network load via every sensing node. In this approach, the sensor nodes were deployed and uniformly distributed randomly, and other nodes were selected as Cluster Heads (CH). Then, to active, the cluster using the cluster scheduling depends on the one-collision domain at any specific time. Next, trackers generated from the source node are transferred to the destination node using multi-hop tree-based routing. Finally, the Pan coordinator was used to modify the data rate of a particular message stream for the disaster management system. However, this system needs more balanced cluster-tree networks.

The strategy for forecasting and preparing for disasters was developed by integrating the time-sensitive real-time sensor devices computation, which was essential to mitigate the adverse disaster effects. Therefore, Pillai et al. [26] proposed the Machine Learning technique to generate the warning signal. This system comprises several sensors, such as MQ4 for methane gas sensing, MQ7 to detect carbon monoxide, and rooftop fissure detection by sensitive resistor sensors. Then, attach every sensor to the control system, representing the sensor nod. The sensor nodes sent the data regarding message frames to the gateway node via Xbee. Then, the sensed detail was sent by the gateway node to the server's time dataset. This data represents the prediction analysis input to generate the warning signals. However, there was no error-free sensed details flow to the network.

The critical contribution of the presented framework is described as follows:

- Initially, the required nodes are created to sense the disaster events.
- A novel JbDBDN is designed and activated in the monitoring environment.
- Consequently, the sensing parameters are upgraded in the jellyfish optimization based on the threshold to sense the fire region and affected people.
- Moreover, in emergency cases, emergency vehicles are operated to help the suffering or affected people.
- Finally, the proposed model was compared with other existing works regarding the delay, energy efficiency, signal loss, and throughput.

The novelty of the presented research is the hybrid of Jellyfish optimization and deep neural network with the WSN for disaster management. The main aim of the presented network is to sense the building fire region and send the information through the WSN to the base station to provide timely service. The proposed model accurately sensed the region of the fire accident to provide quick service and support to the injured people. The model senses the fire accident zone based on parameters such as temperature and smoke and gas content level. The incorporated jellyfish optimization improved the sensing accuracy, and the multi-relay communication facility enhanced the network performance. Also, the proposed model continuously monitors the region to detect disasters.

3. System model and problem statement

WSNs are created and executed in different nations to confirm innovative city reliability. In this structure, the node heads access the information from the other sub-nodes and deliver it to the nearby sink node to deliver it to the base station and inform the user about the disaster crisis. At that time, if the communication speed is slow, it leads to a delay in sending the information in an emergency. The procedure of the WSN in disaster management is shown in Figure 1.

In the past, several works have been studied to enhance the facilities of cities. Disaster management is considered primarily to recreate the regions by minimizing the hazards during natural disasters. WSN takes an active role in disaster management for the sensing and monitoring process. The process has increased the accuracy and achieved more remarkable performance. However, sometimes, it will delay communication, which is a deficit for disaster management architecture. These merits and challenges have inspired the presented study, which is based on disaster management by utilizing the WSN.

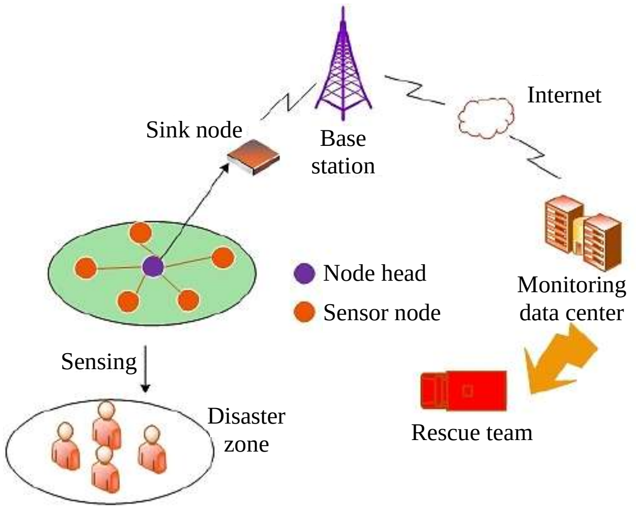


Figure 1 System model and problem statement

4. Proposed methodology

The presented disaster sensing framework is the integration of Jellyfish optimization [27] and deep neural networks. The sensor data are collected and processed in the deep neural framework to detect the disaster region and localization. The disaster prediction process was improved by the Jellyfish function to achieve higher sensing accuracy.

In jellyfish optimization, the jellyfish move towards the region with more food. Similarly, in the presented system, the sensor node senses the fire region based on parameters such as smoke, temperature, and gas content level. Moreover, the activation of the fitness function in the network increases the sensing accuracy. Here, the fitness function was updated until the best solution was acquired. In this research, the finest solution is the exact prediction of the disaster zone and the affected people. The architecture of the presented study is illustrated in Figure 2.

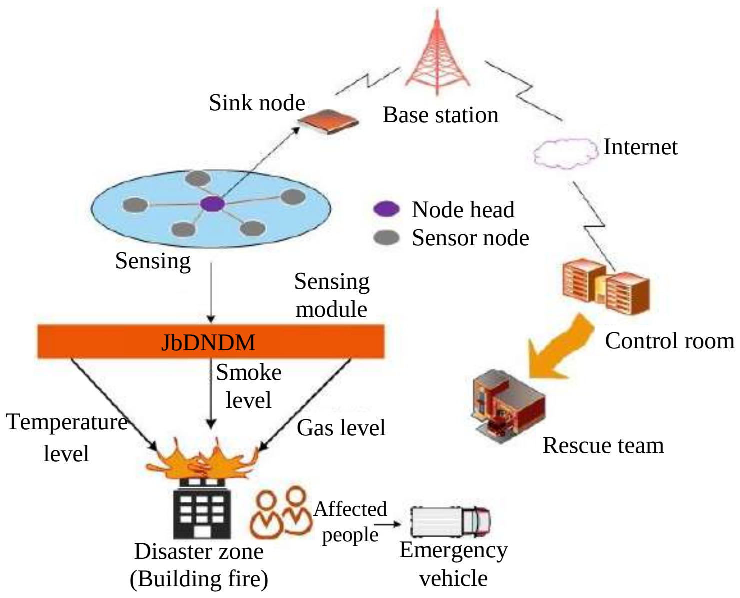


Figure 2 Proposed methodology

In addition, multi-relay communication is activated in the network to increase the communication speed. The multi-relay in the network increases the communication speed and degrades the delay rate. The proposed model utilized multi-relay communication to minimize the transmission power in communication between source and destination, which offers a higher reliability level. Here, the source node communicates to the destination side via multi-relay nodes. In multi-relay communication, the source node initiates the route discovery process by requesting routes to relay nodes through route request packets. Upon receiving the packets, the relay node updates the routing tables and forwards the packet to the other nodes until the destination is reached and establishes a multi-hop path. Then, the data packets are transmitted through the established multi-hop path. The network continuously monitors the health and performance of relay nodes. If a relay node fails or experiences communication issues, the route discovery process is initiated to find an alternative path. It is particularly useful in scenarios where direct communication between the source node and the sink node is not possible due to distance limitations, obstacles, or energy constraints. Multi-relay communication extends the network coverage by establishing multiple communication paths between source nodes and the base station. This is particularly beneficial in large-scale or complex WSN deployments. By distributing the data transmission load among multiple relay nodes, multi-relay communication can reduce the energy consumption of individual nodes, prolonging the overall network lifetime. However, introducing multiple relay nodes into the network increases the overall complexity of the system. This complexity can manifest in the form of managing routing tables, handling multiple communication paths, and ensuring synchronization among nodes. Multi-relay communication introduces additional security challenges, as data packets are handled by multiple nodes, increasing the potential for eavesdropping or data tampering.

4.1 Nodes and network initialization

The present research considers that the rescue teams go to the disaster region to manage the situation and look for survivors. Let us consider n the network environment, the number of nodes utilized for detecting building fires, and the affected people. Here, the nodes are initialized by the framework's deep neural features. The communication between the nodes is explained in Eqn. (1).

$$z_{r_j}n = n_{1r_j}, nY + n_{2r_j} \tag{1}$$

Here, the communication between the nodes is detailed as z, and the relay is denoted as r_j. Here, the WSNs are launched in the region to detect the disaster. In WSN, the nodes are static, identical, and with symmetric radio. Each node employed the GPS to inform the location of the affected zone. The nodes are arranged about the first node. Here, the sensor nodes designed to detect the building fire are scattered and clustered. Each cluster has a node head to transfer the information to the nearby sink node with the GPS location. It sends the received data to the base station, and further, the information is sent to the controller to send the ambulance to the disaster zone to rescue people and manage the disaster hazards.

4.2 Sensing module using JbDNDM framework

The disaster events are detected via network sensor nodes based on the building fire. The sensor nodes are updated with the parameters threshold value to catch the building fire in the sensing module. The parameter includes smoke, temperature, and gas content levels. Furthermore, the jellyfish fitness function is used to see the accurate region of the building fire.

In jellyfish optimization, the jellyfish move towards the region where the greater quantity of food is available, and the food quantity is computed according to location and objective function. Similarly, in the presented system, the sensor node senses the building fire region based on parameters such as smoke, temperature, and gas content level, and the counts of people affected are predicted based on the location and the updated parameters. In this study, the jellyfish fitness function is utilized to sense the disaster zone and the affected people in the disaster zone described in Eqn. (2). Here, the accurate location of the building fire region is sensed by the active motion of the jellyfish.

$$U(t+1) = \frac{U_a + U_b + U_c}{3} \tag{2}$$

Here, U_a is the fitness function to predict the temperature level, U_b the fitness function to predict the smoke level and U_c the fitness function to predict the gas content level. Finally, the addition of the three parameters gives accurate detection.

$$U = \{a, b, c\} \tag{3}$$

Here, U are the sensing parameters of the node, a is the temperature level, b the smoke level, and c the gas content level. The frames of sensing parameters are shown in Eqn. (3).

$$N^U = \{\varphi . U(a, b, c)\} \tag{4}$$

Also, the data sensing process is shown in Eqn. (4). Here N denotes the number of nodes and φ the sensed information. The building fire region is detected based on the threshold value p and the specific level of the parameters q. The fitness function is updated for each parameter. Eqn. (5) estimates the building fire region prediction based on the temperature.

$$U_a = (p(a) > q(a)) \tag{5}$$

Here $p(a)$ is the threshold value of the temperature level $q(b)$ is the sensed level of the temperature, and also the Eqn. (6) estimates the building fire location prediction based on the smoke level.

$$U_b = (p(b) > q(b)) \tag{6}$$

The threshold value of the smoke is indicated as $p(a)$, and the sensed smoke level is denoted as $q(b)$, the Eqn. (7) estimates the prediction based on the gas level.

$$U_c = (p(c) > q(c)) \tag{7}$$

Based on these above-estimated fitness functions, the nodes correctly sense the building fire location and inform the rescue system through WSN. The passive motion of the jellyfish estimated the number of affected people. It is described in Eqn. (8).

$$p = U(t+1).\partial \tag{8}$$

Here, p denotes the affected people and ∂ is the searching variable. Once the disaster zone is identified immediately, the information is shared with the control room or management through the base station of the WSN to provide emergency service to the affected location.

Algorithm 1 JbDNDM

```
Start
{
    int n
    // initialize the number of nodes, n = n_1, n_2, ..... n_i
    Wireless sensor network ()
    z → n
// enabling multi-relay communication for all nodes
    Sensing()
    {
    intY, a, b, c
    Estimate a, b, c                         // parameters estimation
    [a, b, c] → p(a, b, c)                   // initializing threshold state
    Estimate the fitness for each parameter.
    {
    U_a = (p(a) > q(a))
    // fitness of temperature level
    U_b = (p(b) > q(b))
    //fitness of smoke level
    U_c = (p(c) > q(c))
    //fitness of gas content level
    }
    U = disaster   cause
    //Estimating the disaster zone
    //estimating the affected people
    }
    U → r
    // sensed information is sent to the control room
    Emergency services
    }
Stop
```

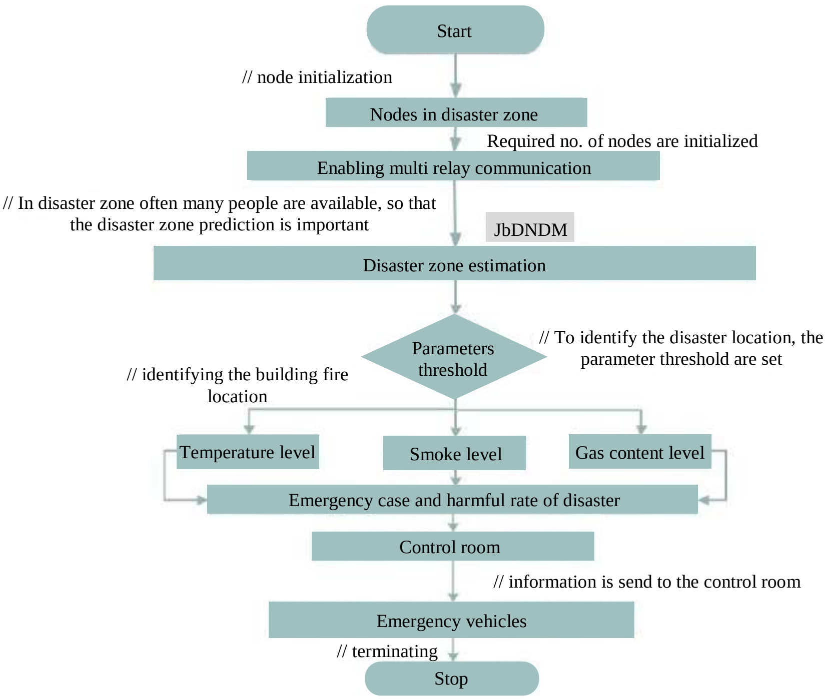


Figure 3 Flowchart JbDNDM

The steps and processes presented in the designed model were detailed in Algorithm 1. The MATLAB tool code was executed based on these step processes, and the results were verified. The algorithm incorporated all mathematical function parameters in the pseudocode format. These processes are given step by step in algorithm 1, and the flow diagram of the designed model is presented in Figure 3.

5. Results and discussion

The suggested technique is designed and executed in the MATLAB tool version R2021a in the Windows 10 OS. The required number of nodes is primarily initialized in the WSN by the in-depth features and the enabled multi-relay communication for faster communication between the nodes. Further, the JbDNDM framework is trained on the WSN nodes to detect the building fire location. Also, to control the maximum energy consumption, the mobility ranges of the nodes are limited. The fitness function of the JbDNDM tracks the building fire zone based on the parameter threshold.

5.1 Case study

Let us assume that a disaster damages one area; immediately, the WSN is activated in the particular region to track the exact location and help the people from the hazard. The components are described in Table 1.

Here, a 20 km range is taken for disaster monitoring, and the multi-relay communication is activated for better communication and to overcome node failure. Also, the threshold value for temperature is 30; smoke is 200, and gas content is 100.

Table 1 Implementation parameters

Wireless Sensor Network	
Number of nodes	0-130
Time to reach	7s
Transmission packet size	1500 bytes
Platform	MATLAB
OS	Windows 10
Sensing parameters	Smoke, Gas content, temperature

The given experimental settings are not suitable for real-life scenarios due to various reasons. The initialized nodes are not enough to cover the large area for monitoring. Then, the assigned packet size is very low for real-world problems. Additionally, the experimental setting only includes smoke, gas content, and temperature as sensing parameters. A real-world fire detection system would also need to be able to sense other factors, such as flame size, heat radiation, and air quality. However, the reasonable point for such settings is smoke, gas content, and temperature are all important parameters to monitor for fire detection. Smoke and gas content can indicate the presence of a fire, and temperature can indicate the severity of a fire. The experimental settings have been used for the real-life problem by increasing the nodes and packet sizes. Also, by changing the sensing parameters, the model can be utilized for the management of other disaster events.

The process of sensing the sending information is detailed in Figure 4. Once the disaster zone is predicted, the location, injured people's report, and the disaster caused are sent to the management or control room, and emergency measures are offered to the affected site. The MATLAB simulation results are shown in Figure 5.

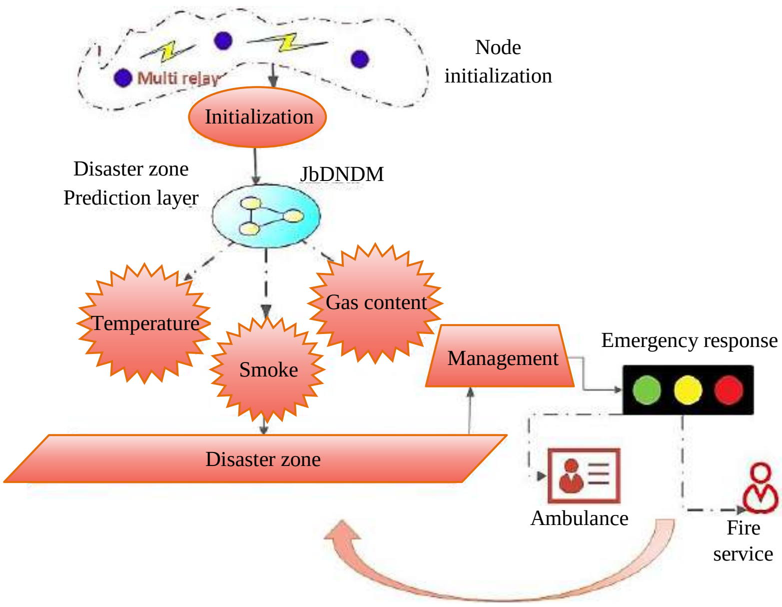
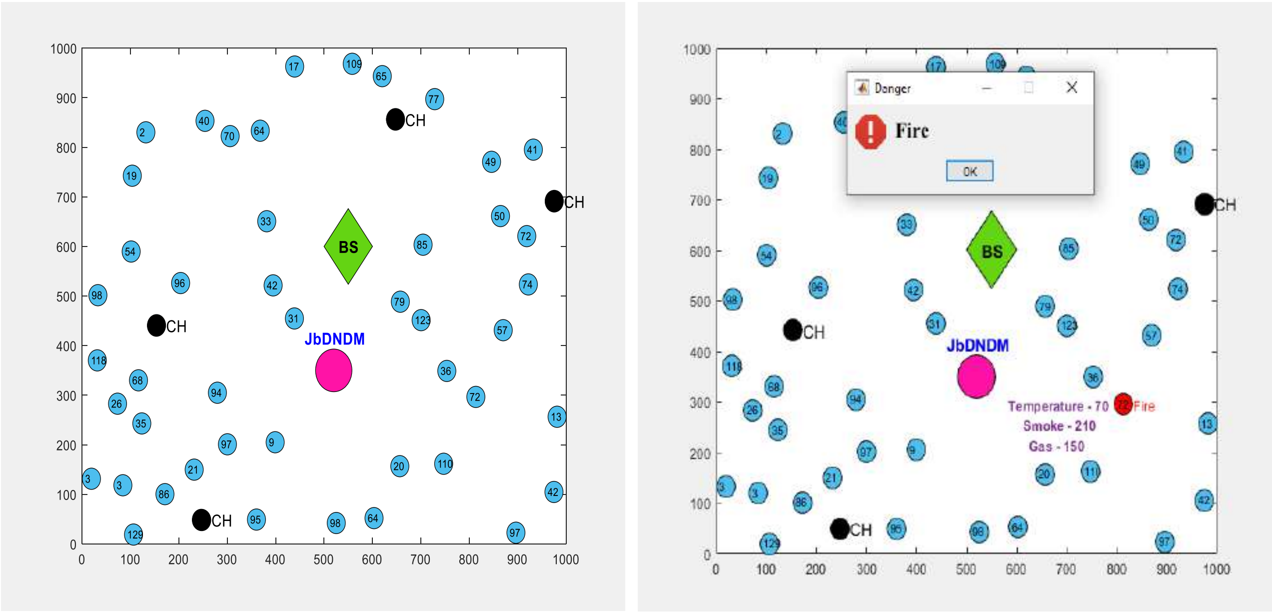


Figure 4 Process of the proposed scheme



(a) (b)

Figure 5 Simulation of the proposed framework: (a) node initialization and clustering, (b) building fire location detection

5.2 Comparative analysis

The proposed JbDNDM model validates its performance metrics: delay, throughput, packet delay ratio, and network lifetime. These metrics were compared with several existing methods, including the Optimized Ensemble Clustering Framework (OECF) [22], Hybrid Multipath Routing Network (HMRN) [28], and Water Wave Optimization (WWO) [29].

5.2.1 Delay

It is defined as the time the network uses to send the information from the source node to the sink node. It is proportional to the distance from the source to the destination node. The calculation of delay is expressed in Eqn. (9).

$$D = \frac{time\ taken\ to\ deliver\ Information\ packets}{total\ packets} \tag{9}$$

The delay rate of the proposed technique is compared to the prevailing methods with a varying number of nodes, such as 20, 40, 60, 80, and 100, in Figure 6. Here, the replica OECF attained the delay rate of 0.087ms, 0.056ms, 0.023ms, 0.06ms, and 0.039ms for each varying node. Also, the HMRN technique obtained 0.025ms, 0.021ms, 0.03ms, 0.034ms, and 0.036ms. WWO acquired delay rates of 0.02ms, 0.025ms, 0.03ms, 0.032ms, and 0.035ms. At the same time, the proposed framework attained 0.018ms, 0.012ms, 0.014ms, 0.015ms, and 0.01ms for the varying number of nodes. Compared to other current WSN techniques, the proposed scheme achieved a minimum delay rate. The comparison assessment for the delay rate is noted in Table 2.

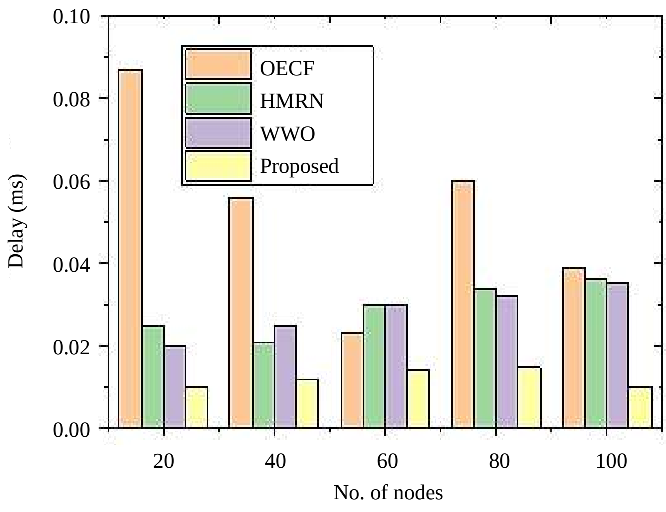


Figure 6 Comparison of delay analysis

Table 2 Assessment of delay metrics

No. of nodes	Delay (ms)			
	OECF	HMRN	WWO	Proposed
20	0.087	0.025	0.020	0.018
40	0.056	0.021	0.025	0.012
60	0.023	0.030	0.030	0.014
80	0.060	0.034	0.032	0.015
100	0.039	0.036	0.035	0.010

5.2.2 Throughput

It is the entire amount of data packets transferred during the transmission process in the WSN at a specific time. Eqn. (10) estimates the throughput calculation.

$$T = \frac{arrived\ packets}{simulation\ time} \tag{10}$$

The existing models, such as OECF HMRN and WWO, attained the throughput of 40.34 Kbps, 42 Kbps, and 25 Kbps for 20 nodes, 79.707 Kbps, 51.5 Kbps and 23.9 Kbps for 40 nodes, 58.824 Kbps, 62.4 Kbps, and 22.1 Kbps for 60 nodes, 49.622 Kbps, 70 Kbps, and 22.1 Kbps for 80 nodes and 54.44 Kbps, 80 Kbps and 22 Kbps for 100 nodes. At the same time, the proposed framework gained a throughput of 79.25 Kbps for 20 nodes, 79.17 Kbps for 40 nodes, 70.12 Kbps for 60 nodes, 62.58 Kbps for 80 nodes, and 80.01 Kbps for 100 nodes. Here, the proposed framework gained the maximum throughput. The comparison of the throughput is validated in Table 3 and Figure 7.

Table 3 Assessment of Throughput Metrics

No. of nodes	Throughput (Kbps)			
	OECF	HMRN	WWO	Proposed
20	40.34	42.0	25.0	79.25
40	79.70	51.5	23.9	79.17
60	58.82	62.4	22.7	70.12
80	49.62	70.0	22.1	62.50
100	54.44	80.0	22.0	80.01

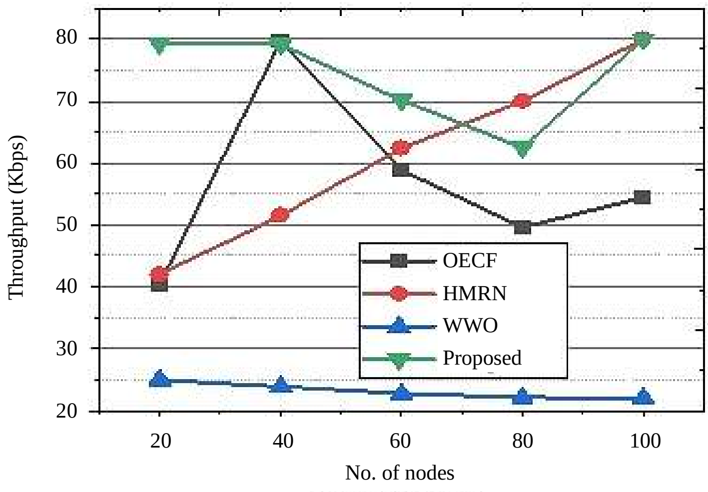


Figure 7 Comparison of Throughput Analysis

5.2.3 Packet Delivery Ratio (PDR)

It is calculated by dividing the number of information packets delivered from the source node by the total packet counts arriving at the destination node. The calculation of the packet delivery ratio is shown in Eqn. (11).

$$PDR = \frac{received\ packets}{delivered\ packets} \tag{11}$$

The rate of PDR with the respective number of nodes is shown in Figure 8. Here, the replica OECF attained the packet delivery ratio of 87.5%, 30.28%, 70.83%, 42.51%, and 78.18% for each varying node, such as 20, 40, 60, 80, and 100. Also, the technique HMRN obtained 95%, 94%, 93%, 92% and 91%. WWO acquired delay rates of 90%, 98%, 97%, 96%, and 94%. At the same time, the proposed framework attained 99%, 99.4%, 99.5%, 98.6%, and 99.7% for the varying number of nodes. Compared to other current WSN techniques, the proposed scheme achieved a maximum packet delivery ratio. The comparison assessment for the PDR is noted in Table 4.

Table 4 Assessment of PDR metrics

No. of nodes	PDR (%)			
	OECF	HMRN	WWO	Proposed
20	87.50	95	90	99.0
40	30.28	94	98	99.4
60	70.83	93	97	99.5
80	42.51	92	96	98.6
100	78.18	91	94	99.7

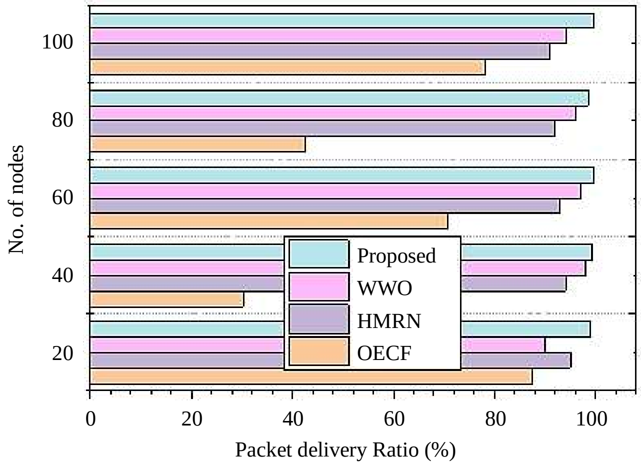


Figure 8 Comparison of Packet Delivery Ratio Analysis

5.2.4 Network lifetime

The count of the active sensor nodes and the route sustainability of the sensor network estimate the life span of the network. It is also defined as the duration for the few nodes to die.

Table 5 Assessment of Network Lifetime Metrics

No. of nodes	Network Lifetime (h)			
	OECF	HMRN	WWO	Proposed
20	62.5	25.2	24.0	69.0
40	37.8	24.8	18.5	72.5
60	42.0	23.4	16.4	73.0
80	68.1	22.5	15.2	74.5
100	65.5	21.8	14.9	75.0

The existing models, such as OECF HMRN and WWO, attained a network lifetime of 62.5 h, 25.2 h, and 24 h for 20 nodes, 37.8 h, 24.8 h and 18.5 h for 40 nodes, 42 h, 23.4 h and 16.4 h for 60 nodes, 68.1 h, 22.5 h and 15.2 h for 80 nodes and 65.5 h, 21.8 h and 14.9 h for 100 nodes. At the same time, the proposed framework gained a throughput of 69 h for 20 nodes, 72.5 h for 40 nodes, 73 h for 60 nodes, 74.5 h for 80 nodes, and 75 h for 100 nodes. Here, the proposed framework gained the maximum throughput. The comparison of the throughput is validated in Table 5 and Figure 9.

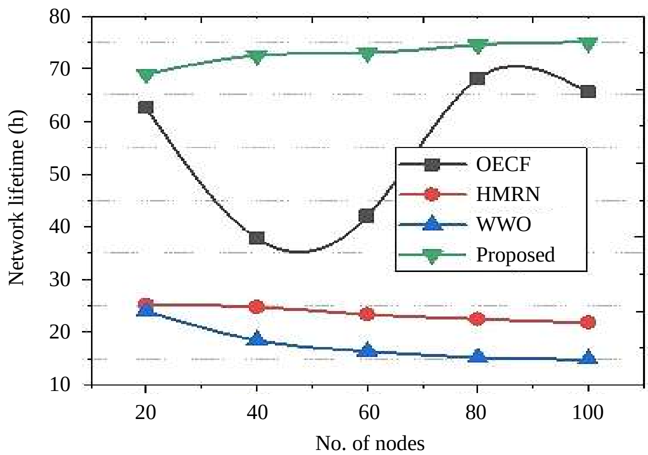


Figure 9 Comparison of Network Lifetime Analysis

The metrics of the JbDNDM framework, such as PDR, throughput, network lifetime, and delay, are compared with a few current techniques based on WSN. The overall comparison of the proposed and the prevailing frameworks is recorded in Table 6. The comprehensive statistics proved that the presented framework achieved more outstanding results for the throughput, network lifetime, and PDR; the delay in communication decreased.

The activation of multi-relay communication between the nodes has increased communication speed and reduced delay. There are no trade-offs or considerations associated with achieving these performance metrics.

Table 6 Performance evaluation of the proposed technique

Techniques	Metrics			
	Delay (ms)	**Throughput (Kbps)**	**PDR (%)**	**Network Lifetime (h)**
OECF [22]	0.039	54.44	78.18	65.5
HMRN [28]	0.036	80	91	21.8
WWO [29]	0.035	22	94	14.9
Proposed	0.01	80.01	99.7	75

The employed multi-relay communication in the presented architecture selected the optimal relay nodes that can transmit the sensed information. These relay nodes ensure reliable data transmission and increase the throughput percentage of the network. The chosen relay nodes can also minimize the delay rate. The multi-relay communication adapts the routing path based on the disruption, which avoids the data traffic during its transmission. In disaster management frameworks based on Wireless Sensor Networks (WSNs), throughput and delay rate play crucial roles in ensuring the effectiveness and timeliness of disaster response and recovery efforts.

5.2.5 Sensing accuracy

In addition to the network performance, the efficiency of the proposed model is validated using the sensing accuracy metrics. Here, the sensing accuracy of the JbDNDM framework for various numbers of nodes is validated and compared with the prevailing frameworks. In the presented system, the sensing accuracy is measured through training and testing of the smoke dataset taken from the Kaggle site. The jellyfish best solution search factors increased the sensing accuracy of the model. However, the model required excess data to train which cause over fitting and poor generalization. The comparison for the sensing accuracy is illustrated in Figure 10.

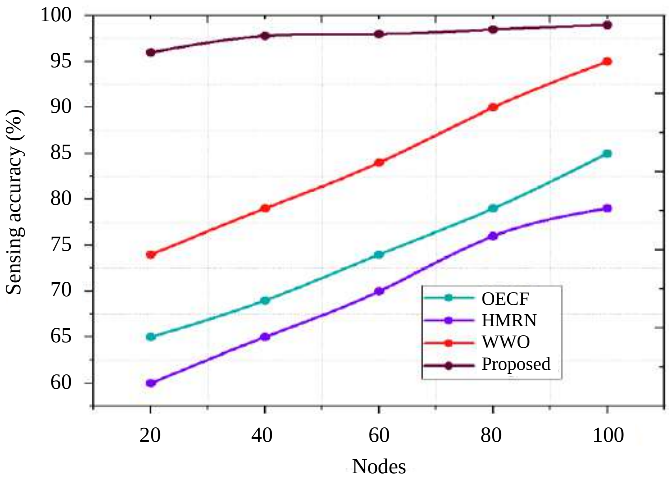


Figure 10 Sensing accuracy comparison

Here, the sensing accuracy of the model OECF for 100 nodes is 85%, HMRN is 79%, and WWO is 95%. Besides, the sensing accuracy of the presented JbDNDM is 98.5%, which is higher than the sensing accuracy of the other models. Therefore, the proposed model effectively detected the fire accident region and provided timely service with the operation of the WSN environment.

5.3 Discussion

The validation of overall metrics proved that the developed framework gained the finest results for all metrics. Hence, the framework presented is satisfactory for disaster management to support the people injured from the disaster. Also, it enhances the smart city facilities. The performance of the given scheme is recorded in Table 7.

Table 7 Performance of the proposed JbDNDM

Overall performance statistics	
Delay	0.01ms
Throughput	80.01Kbps
PDR	99.7%
Network Lifetime	75sec

For 100 nodes, the presented framework acquired a greater accuracy rate of 99%. Also, for nodes 20, 40, 60, and 80, the accuracy rate is 96%, 97.8%, 98% and 98.5%. It shows that the suggested technique correctly predicts the disaster zone. The detailed evaluation of the assessment results shows the efficiency of the presented scheme in disaster management. The designed JbDNDM is a comprehensive framework that covers all aspects of disaster management, from early warning to disaster response and recovery. The proposed model converged more rapidly than the other algorithms, which returns precise results within a short duration. The model can be deployed in a variety of environments, such as urban areas, forests, and remote areas. However, it can be expensive to deploy and maintain in real-world problems. The model is complex to design and configure. Also, it can be vulnerable to interference from environmental factors and malicious attacks.

6. Conclusion

The disaster caused severe damage to the lives of human beings because of the sudden attack and lack of ready measures. So, a novel framework is designed to manage the building fire disaster. Here, the management started with initializing nodes in the network and activated the JbDNDM framework at the sensing module for accurate disaster prediction. In many cases, the WSN provides low-speed communication, so to attain better communication, multi-relay communication is enabled. Finally, the performance metrics were validated and compared with other current techniques. The designed approach reached a higher rate of 80.01Kbps throughput and a lower delay rate of 0.01ms. Also, the sensing accuracy of the suggested process is increased to 99% for 50 nodes. Thus, the designed novel framework is more effective for disaster management for predicting the disaster, region, and affected people. However, the WSN system is vulnerable to communication interference due to the presence of security threats. So, in the future, the disaster management model will be extended to reduce the security issues faced by the WSN environment during packet transmission or communication.

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