

Transformer-Assisted Robotic MANET Routing for Disaster Response Using Secretary Bird Optimization

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ABSTRACT: Rapid and reliable communication are important for Disaster Response (DR), where existing communication infrastructure become severely degraded. However, robotic Mobile Ad Hoc Networks (MANET) deployed in disaster environments face dynamic topology changes, unstable communication links, limited residual energy, node mobility, congestion, and frequent route failures. To overcome these issues, this paper proposes a Transformer-Assisted Robotic MANET Routing framework for DR using Secretary Bird Optimization (SBO). The collected MANET data is delivered to SBO module, which identifies suitable candidate relay robots by evaluating their fitness and jointly optimizing robot selection and energy-aware routing decisions. Subsequently, a Robotic Cluster formation layer selects appropriate leader robots, assigns relay nodes, and establishes a reliable communication backbone among the robotic agents. A Transformer Learning Module is then employed to extract significant network features through attention-based learning and model the temporal dependencies of changing network states for route prediction. Experimental result is implemented in OMNet++, the effectiveness of the proposed framework is assessed using Packet Delivery Ratio (PDR) of 60%, delay of 0.02s, energy consumption of 30%, and throughput of 7600 packets/s for intelligent DR operations. The proposed framework provides reliable data delivery, low-latency communication, efficient energy utilization, and high data transmission capability, during time-critical DR operations.

Keywords: Disaster Response, robotic MANET, Secretary Bird Optimization, Robotic Cluster Formation Layer, Transformer Learning.

1. Introduction

DR robotic MANET employs rescue robots, UAV, and mobile sensor nodes to establish a temporary wireless network in areas where communication infrastructure is damaged [1]. MANET is a network made up of mobile nodes that automatically communicate, and change their

positions and network connections without depend on fixed infrastructure [2]. Consequently intelligent routing is then used to dynamically discover and maintain reliable communication paths for timely transmission of emergency data [3]. MANET on Route Request (RREQ) dissemination is used to discover communication

paths and improve network reachability [4]. For these issues several optimization techniques are utilized for DP in MANET [5-6]. Moreover, MANET operation in Game-Theoretic Structure is used for secure and dependable process. However, it takes more optimization, large computational time [7]. By addressing the limited availability of effective algorithms for DP in the MANET environment, this study proposes a solution to improve the routing and overall efficiency of MANET for DP.

2. Related Work

In recent years, numerous algorithms have been developed to improve optimization performance in MANET and solve challenging optimization problems. In [8] Arulselvan and Rajaram have proposed a Dolphin Echolocation Optimization (DEO) and Cat Swarm Optimization (CSO) algorithm in MANET to optimize routing decision. It provides good exploration of complex search spaces. However, it suffers from premature convergence. Consequently, in [9] Hao et al have presented Adaptive Communication Recovery Algorithm (ACRA) robot-assisted in disaster circumstances. It is suitable for MANET where nodes generally move and network connections change. Nevertheless, frequent route reconstruction consumes extra energy at mobile nodes. Additionally in [10] Hassan et al have developed Multi-Objective Optimization with Long Short-Term Memory (MOO-LSTM) based trust prediction to enhance routing decisions in MANET. LSTM-based trust prediction identifies malicious nodes. Nonetheless, frequent trust prediction and optimization consume additional energy at MANET nodes. Furthermore, in [11] Adam et al have proposed Long-Term Evolution (LTE) technology, Affinity Propagation Clustering (APC), graph theory, and a Genetic Algorithm (GA) for DP in MANET. APC automatically identifies suitable node clusters without requiring a predefined number of clusters. However, repeated clustering and GA-based route optimization increase battery usage. Moreover, in

[12] Raj et al invented Artificial Neuro-Fuzzy Inference System (ANFIS) with an Improved Elephant Herd Optimization (IEHO) in robotic MANET to achieve adaptive routing. Nevertheless, communication overhead increase significantly as the number of robotic nodes grows. To overcome these limitations this paper proposes a Transformer-Assisted Robotic MANET Routing structure for DP using SBO.

2.1 Layout of the Contribution

The proposed SBO module, which identifies suitable candidate relay robots by evaluating their fitness and jointly optimizing robot selection and energy-aware routing decisions. A Transformer Learning Module is then developed to extract significant network features through attention-based learning and model the temporal dependencies of changing network states for route prediction.

3. Proposed System

For quick DP communication in MANET a Transformer-Assisted Robotic MANET Routing framework using SBO is proposed. At first, the DP robotic MANET collects essential disaster information, containing victim locations, emergency alerts, environmental conditions, and sensor readings. Network-state information like residual energy, link quality, node mobility, communication distance, and traffic load is monitored to understand the dynamic network conditions. The collected network parameters are fed to the SBO module, which performs candidate relay discovery, fitness evaluation, optimal robot selection, and energy-aware node optimization. Based on the optimized relay nodes, the Robotic Cluster Formation Layer chooses suitable leader robots, assigns relay nodes, and establishes a reliable communication backbone. Subsequently, the Transformer Learning Module removes significant network features and applies an attention mechanism to learn complex network-state relationships and calculate appropriate routing paths. The information is forwarded to the

Intelligent Disaster Routing Engine, which performs reliable path selection, dynamic route adaptation, congestion avoidance, and fault-tolerant routing. The routes are used by the Emergency Data Transmission Layer to efficiently deliver rescue messages, medical

information, disaster updates, and control commands. The DR Coordination layer supports rescue-team communication, victim tracking, and resource allocation. Figure 1 shows the block diagram for proposed work.



Figure 1: *Block diagram for proposed work*

3.1 Disaster Information

For DP the disaster information contains victim location information it provides the positions of trapped, injured, detected individuals and supports rescue groups to prioritize and coordinate rescue operations. Emergency alerts characterise time-critical events like fire outbreaks, hazardous gas detection, communication failures to human life and robotic nodes. The environmental information defines the changing physical conditions of the disaster-affected area, containing temperature, smoke concentration, gas levels, water level, and humidity. Sensor readings deliver continuous measurements collected by sensors arrayed on robots, and MANET. The disaster information is forwarded to network state information.

3.2 Network State Information

Network state information provides an emergency communication to each network states. The residual energy represents the remaining battery power of a rescue robot. Link quality delivers a wireless connection between two nodes in the disaster area. Node mobility signifies the rescue

robots continuously move through the disaster area. The communication distance is function as the physical distance between communicating nodes. Traffic load defines the amount of data currently being queued at a node. The collected network parameters are fed to SBO module.

3.3 Secretary Bird Optimization Module

For DP in MANET, the SBO module collects network parameters to identify dependable relay robots and construct energy-efficient communication routes. The random initialization of the SB positions in the search space is expressed as

$$X_{i,j} = lb_j + r \times (ub_j - lb_j) \quad (1)$$

Where, X_i signifies the position of the i^{th} SB in the search space, ub_j, lb_j represent the lower and upper bounds of the j^{th} dimension, r indicates randomly generated value among 0 and 1.

$$t < \frac{1}{3}T, x_{i,j}^{newP1} = x_{ij} + (x_{random_1} - x_{reandom_2}) \times R_1 \quad (2)$$

$$X_i = \begin{cases} X_i^{new,P1}, F_i^{new,P1} < F_1 \\ X_i, \text{else} \end{cases} \quad (3)$$

Here, t signifies the present iteration, T denotes the maximum number of iterations. $X_i^{new,P1}$ indicates the efficient location of the

i^{th} SB through the initial phase. The variables $x_{random_1}, x_{reandom_2}$ denote randomly selected candidate solutions. Figure 2 displays the flowchart for SBO.

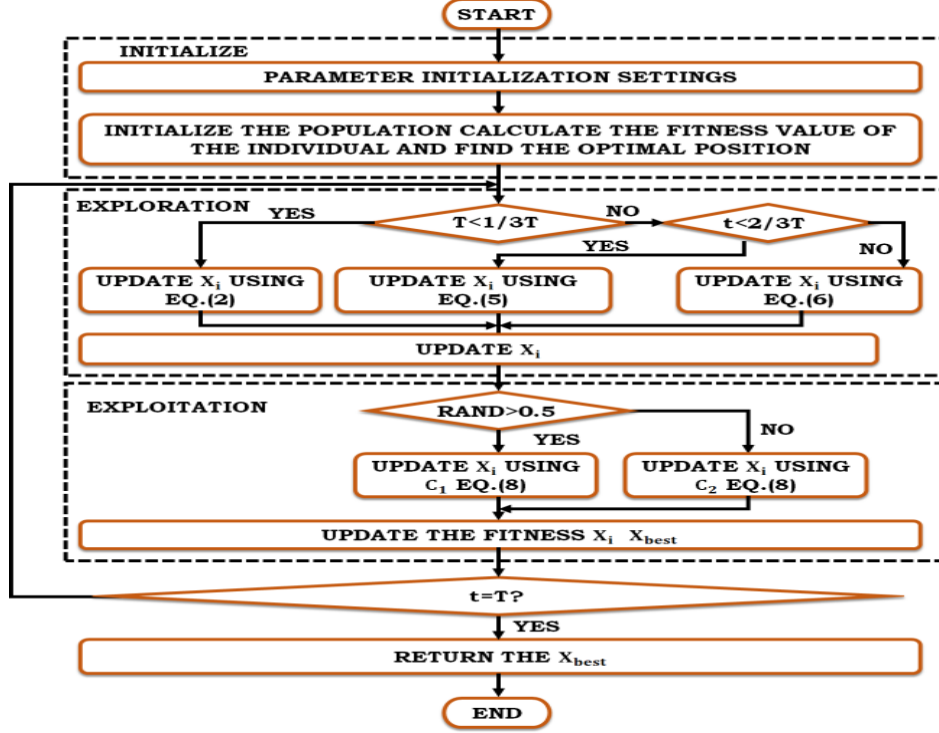


Figure 2: Flow chart for SBO

Updating the location of the SB during the prey-consumption stage

$$RB = randn(1, Dim) \quad (4)$$

$$\frac{1}{3}T < t < \frac{2}{3}T, X_i^{new,P1} = x_{best} + \exp\left(\left(\frac{t}{T}\right) \wedge 4\right) \times (RB - 0.5) \times (x_{best} - x_{i,j}) \quad (5)$$

$$t > \frac{2}{3}T, X_i^{new,P1} = x_{best} + \left(\left(1 - \frac{t}{T}\right) \wedge \left(2 \times \frac{t}{T}\right)\right) \times x_{i,j} \times RL \quad (6)$$

$$RL = 0.5 \times Levy(Dim) \quad (7)$$

Escape based search strategy of SB during exploitation is

$$X_i^{new,P2} = \begin{cases} C_1: x_{best} + (2 \times RB - 1) \times \left(1 - \frac{t}{T}\right)^2 \times x_{i,j} \text{ if } r \text{ and } < r_i \\ C_2: x_{i,j} + R_2 \times (x_{random} - K \times x_{i,j}), \text{else} \end{cases} \quad (8)$$

Here, $r = 0.5$, R_2 indicates a randomly generated $(1 \times Dim)$ array sampled from a normal delivery, x_{random} signifies a randomly selected applicant

resolution from the current iteration, K specifies randomly chosen integer used to control the position-update process. The SBO collects the network parameters and fed to robotic cluster formation layer.

3.4 Robotic Cluster Formation Layer

For DR Robotic Cluster Formation layer identifies the robot to performance as the cluster leader. It allocates other robots as relay nodes based on their energy, distance, connectivity, and communication quality. The selected leader coordinates communication and data exchange among robots within the cluster. This process establishes a energy-efficient communication backbone for DR operations.

3.5 Transformer Learning Module

Transformer learning module selects the most important network-state features. The transformer

based self-attention mechanism is to improve the DR in MANET by concentrating on the most appropriate features inside compound network. The attention mechanism in transformers allows the model to weigh the position of dissimilar input

features thus capturing long-range dependences and complex interactions among routes. Figure 3 displays the transformer self-attention mechanism.

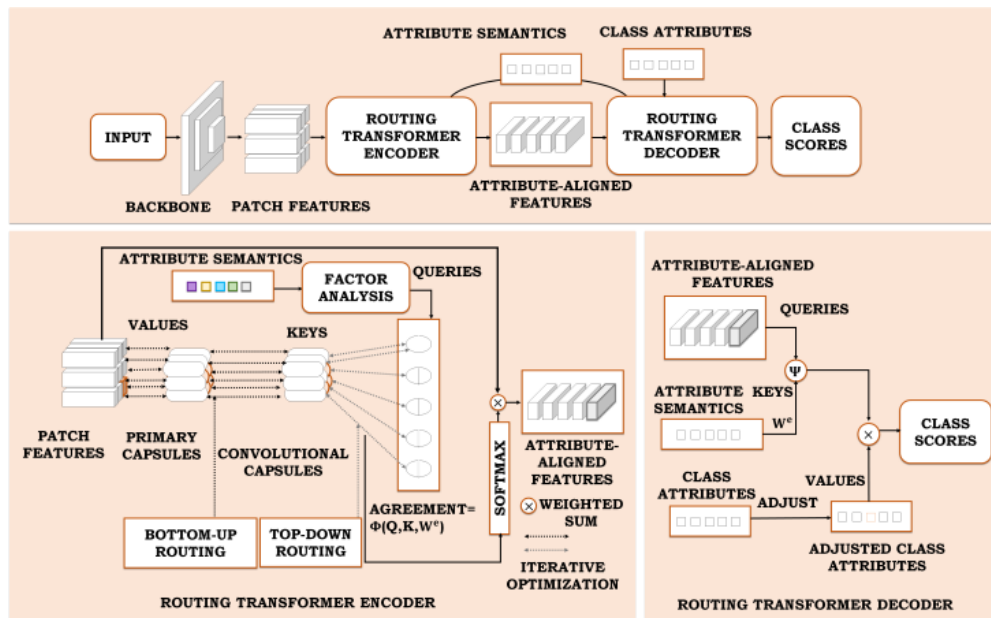


Figure 3: Transformer self-attention mechanism

In a transformer, self-attention is computed using scaled dot-product attention, which is defined by the following equation:

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V \quad (9)$$

Here, Q denotes query matrix, K indicates key matrix, V represent value matrix and d_k specifies dimension of the key vectors. The transformer-based attention identifies network by dynamically selecting the network state for prediction, it is fed to intelligent disaster routing engine.

3.6 Intelligent Disaster Routing Engine

The intelligent disaster routing engine collects the processed network information and calculates the presented communication paths. It selects consistent routes by considering factors like energy level, link quality, distance, and network stability. It dynamically changes routes when congestion, mobility, avoids communication bottlenecks, it provides a fault-tolerant routing, and maintaining data delivery even when some

robotic nodes become unavailable at last it is fed to emergency data transmission layer.

3.7 Emergency Data Transmission Layer

The emergency data transmission layer is used for delivering information quickly during DR. It transmits rescue messages, medical information, and disaster updates between robots, rescue teams, and control centers. It delivers control commands to coordinate robotic activities and adjust rescue operations in real time. At last it provides a fast and effective emergency response to DR Coordination layer.

3.8 Disaster Response Coordination Layer

The DR coordination layer tracks the location and status of victims using information collected from robots and sensing devices. It supports resource allocation by identifying medical supplies, rescue robots, personnel, and other resources are most

urgently required. DR layer improves coordination, response speed, and efficient utilization of resources during disaster recovery.

4. Experimental Result and Discussion

To access DR in MANET, implementation in executed in OMNeT++ simulation by proposed Transformer-Assisted Robotic MANET Routing for DR using SBO.

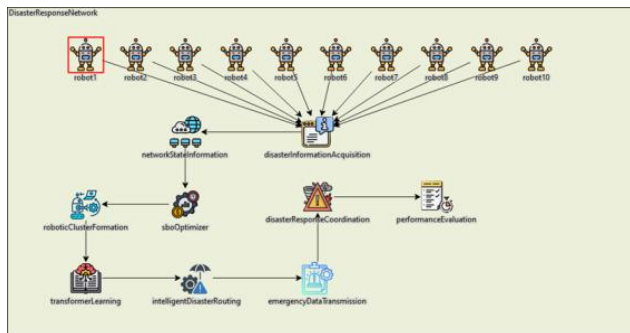


Figure 4: OMNeT++ simulation environment

Figure 4 displays OMNeT++ simulation environment. The multiple robots robot1 to robot10 fed telemetry and observations into disaster information acquisition, which coordinates with network state information. The system optimizes resources through SBO and groups the units using robotic cluster formation.

Data is processed through transformer learning to establish intelligent disaster routing. At last the operation finish in emergency data transmission and DR coordination.

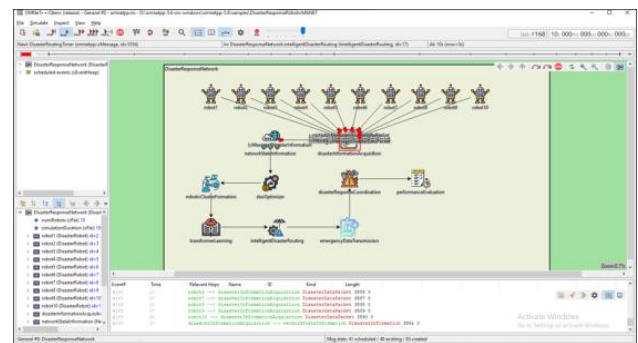


Figure 5: OMNeT++ simulation runtime

Figure 5 shows the OMNeT++ simulation runtime. The ten robotic nodes collect disaster-related information and forwarded to the disaster information acquisition module. The SBO-based cluster formation selects suitable robotic nodes based on their network conditions. Transformer based routing extracts important local and global network features, intelligent disaster routing module to select reliable routes when network conditions change it assesses the overall network performance.

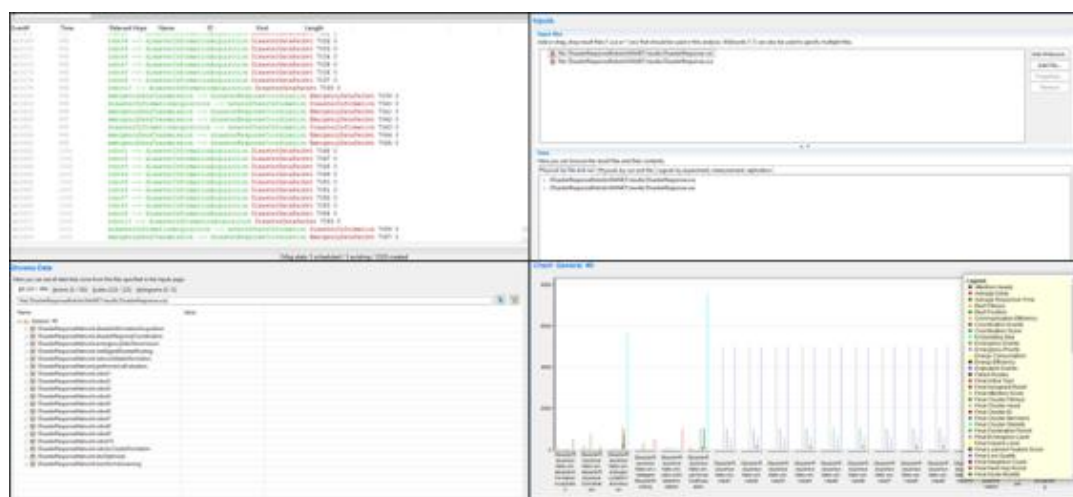


Figure 6: (a) OMNeT++ simulation event log window, (b) Input, (c) Browse data, (d) General #0

Figure 6 (a) displays the OMNeT++ simulation event log window for response robotics MANET. It shows the sequential simulation events, module hops for robot 1 to robot 10. Figure 6 (b) displays the input specified to find the DR in robotic

MANET. Figure 6 (c) shows browse data it provides classified scalar and vector modules, statistics, and run details. Figure 6 (d) displays general #0 with y-axis denotes metric values ranging to 8,000 for each nodes it is varying.

Attention heads, average delay, average response time, coordination score, and energy consumption are calculated for DR.

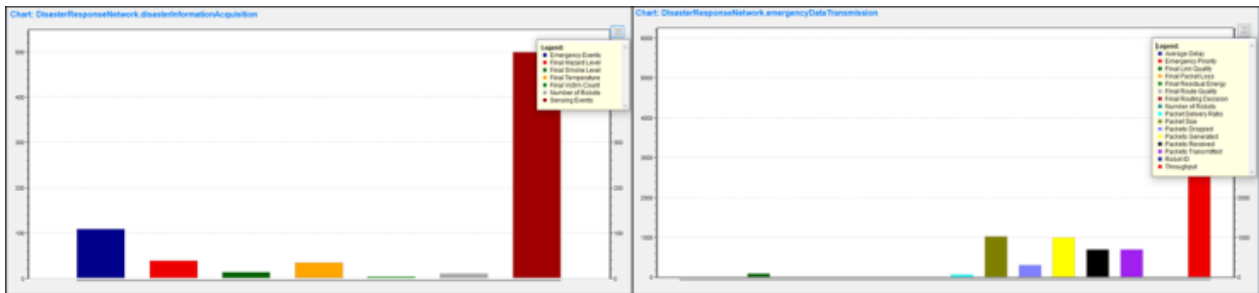


Figure 7: (a) Disaster response network disaster information acquisition, (b) disaster response network emergency data transmission

Figure 7 (a) displays disaster response network disaster information acquisition. Emergency events indicated in blue colour it is situated above 100. Figure 7 (b) shows disaster response network

emergency data transmission. PDR of 50, packet generated is 1000, packet received and packet transmitted is 700, and throughput is 2500 for DR when data is transmitted.

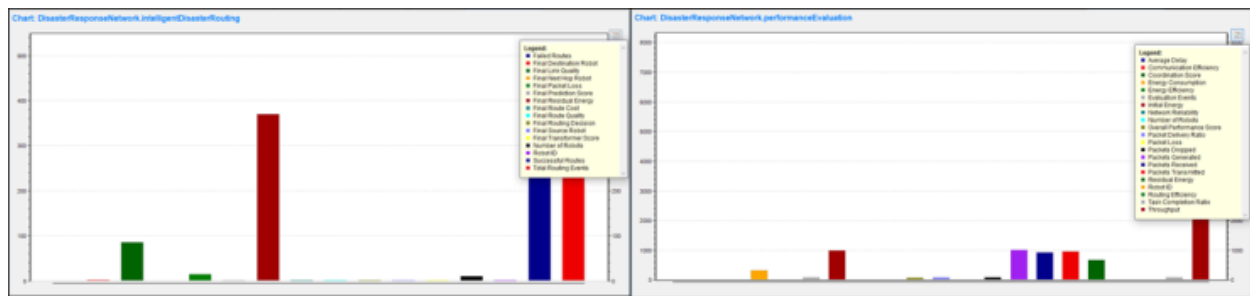


Figure 8: (a) DR network intelligent disaster routing, (b) DR network performance evaluation

Figure 8 (a) displays DR network intelligent disaster routing. It shows routing- metrics, final route cost is around 370, total routing events is above 200 indicating intelligent routing. A green colour shows a moderate value which is around 90 for final next hop count for DR. Figure 8 (b) shows DR performance metrics with energy consumption of 320 evaluation events of 100,

initial energy of 1,000, number of robots performance score of 70. PDR of 100, packets dropped of 80 units, packets generated of 1,000, packets received of 920, packets transmitted of 960, residual energy of 660, task completion ratio of 100 units and throughput of above 2,000 for DR network.

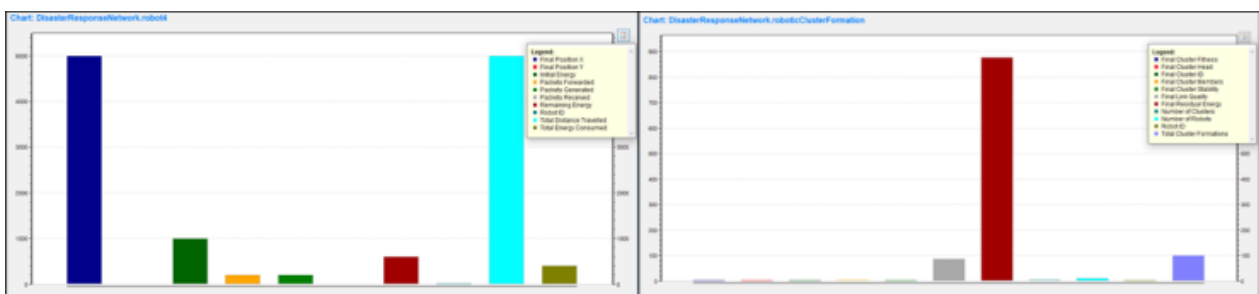


Figure 9: (a) DR network robot 4, (b) DR network robotic cluster formation

Figure 9 (a) shows the DR network robot 4, the final position X and robot ID have the value of 5000, packets forwarded is 1,000, initial energy, total distance travelled and packet generated have low values, remaining energy is 600 when the robot 4 on the DR network. Figure 9 (b) displays DR network robotic cluster formation, the final cluster metric is high which is near 875 to 900 and other cluster members, link quality, robot ID are near 90 which is very low for DR formation.

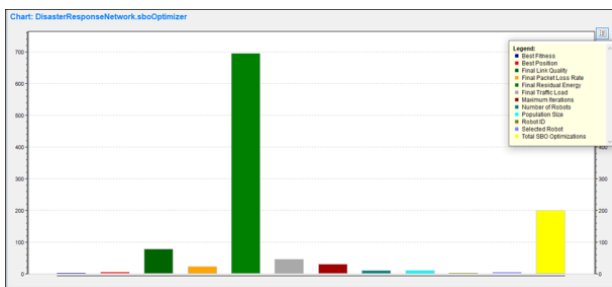


Figure 10: DR network SBO optimizer

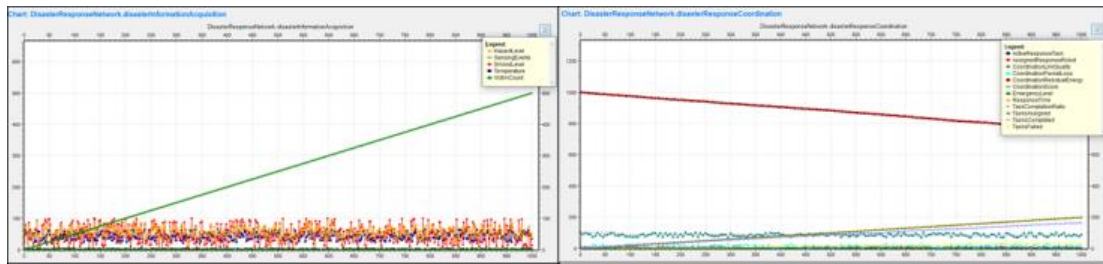


Figure 11: (a) DR network disaster information acquisition, (b) DR network DR coordination

Figure 11 (a) shows DR network disaster information acquisition. The sensing events metric demonstrate a clean, continuous linear increase up to 500, indicating a cumulative counter that increments constantly over the simulation run. Smoke level, hazard level, and temperature oscillate quickly within a lower band (0–100),

representing fluctuating environmental sensor readings. Figure 11 (b) shows a steady, linear increase in starting and climbing to a value of approximately 200 by the 1000. DR network remain consistently low, fluctuating roughly between the 50 and 100 range on the vertical axis throughout the entire simulation run for DR.

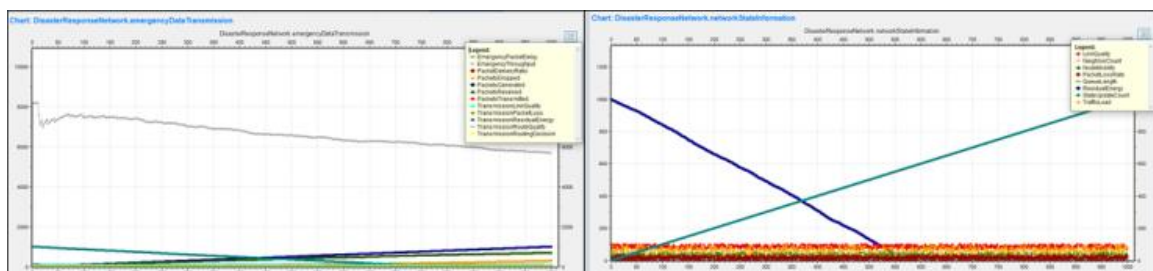


Figure 12: (a) DR network emergency data transmission, (b) DR network state information

Figure 12 (a) displays DR network emergency data transmission. The data transmission for

packet generated and received begins with high variability around 8,000, stabilizes, and then

steadily declines toward 6,000 by the end of the simulation, it rising linearly toward 1,000 for transmission residual energy. Figure 12 (b) shows DR network state information. The state updates count increases linearly reaching nearly 1000 by the end of the simulation. Link quality, packet loss rate, queue length, and traffic load remain densely packed near 100 throughout the entire run for DR network information.

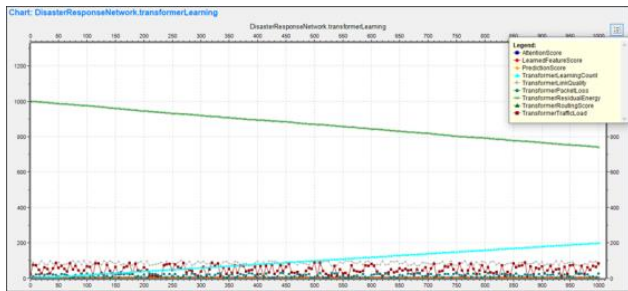


Figure 13: DR network transformer learning

Table 1: Comparison with the proposed technique

Study	PDR (%)	Delay (s)	Energy consumption (%)	Throughput (packets)
Hassan et al [10]	34	0.7	56	443
Bali et al [5]	11.6	0.36	69.4	-
Kampitaki et al [4]	55	0.54	-	-
Proposed Work	60	0.02	30	7600

In the comparison table 1 Hassan et al [11] have the PDR of 34%, delay of 0.7s, energy consumption of 56%, throughput of 443 packets, Bali et al [5] have the PDR of 11.6%, delay of 0.36s, energy consumption of 69.4%, Kampitaki et al [4] have the PDR of 55%, delay of 0.54s, and proposed technique have the PDR of 60%, delay of 0.02s, energy consumption of 30%, and throughput of 7600 packets/s.

5. Conclusion

In this paper a Transformer-Assisted Robotic MANET Routing framework for DR using SBO is proposed to achieve energy-efficient communication among robotic nodes. The SBO module evaluates network conditions and identifies suitable relay robots whereas optimizing robot selection and energy-aware routing decisions. The robotic cluster formation layer utilizes an effective communication structure by

Figure 13 shows the DR network transformer learning. The transformer learning count steadily increases up to 200, transformer traffic load fluctuating, oscillating between 100. Network performance and prediction scores remain flat and close to zero near the baseline for DR in MANET.

Comparison with the proposed technique

In the evaluation with proposed technique the proposed Transformer-Assisted Robotic MANET Routing framework for DR using SBO method is compared with the existing techniques as presented in table 1.

selecting leader robots and assigning relay nodes. The transformer learning module captures important network characteristics and temporal variations in network states, supporting more effective route prediction and adaptation. Experimental result is implemented and evaluated using OMNeT++, achieving a PDR of 60%, a delay of 0.02 s, energy consumption of 30%, and a throughput of 7600 packets/s. These results validate that the proposed structure provide reliable PDR, low-latency communication, efficient energy utilization, and high data-transmission capability, it is suitable for intelligent and dynamic DR operations. Future work focuses on investigate reinforcement learning and federated learning techniques to allow adaptive routing decisions under continuously changing network conditions without relying heavily on centralized control.

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