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RESEARCH ARTICLE

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CAPSULSTM-BOA: A HYBRID DEEP LEARNING AND BIO-INSPIRED ROUTING MODEL FOR MOBILE AD-HOC NETWORK

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ABSTRACT

Establishing consistent, adaptable connectivity in infrastructure-free situations is a significant challenge for decentralized mobile communication. This research article presents a unique hybrid routing system that blends bio-inspired optimization and Deep Learning (DL) for Android-based Mobile Ad-Hoc Networks (MANETs). Proposed framework combines Long Short-Term Memory (LSTM) network for describing temporal fluctuations in node mobility, link reliability, and traffic patterns, with a Capsule Network to extract high-level spatial correlations in network architecture. The system uses the Bonobo Optimization Algorithm (BOA), which is modelled after the social intelligence and cooperative behavior of bonobos, to choose the best routing paths dynamically. By striking a balance between exploration and exploitation, BOA assesses routing choices based on important variables such as transmission delay, node movement, energy levels, and link quality. Even in the face of quickly shifting topologies, highly adaptive, real-time peer-to-peer communication is made possible by the combination of CapsuLSTM and BOA. According to simulation results, the proposed CapsuLSTM-BOA framework offers a potent solution for file sharing, mobile collaboration, and resilient communication in decentralized networks, outperforming conventional MANET routing protocols in terms of end-to-end delay, throughput, Packet Delivery Ratio (PDR), packet loss ratio, energy consumption, end-to-end delay, routing control overhead and network lifetime.



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I. INTRODUCTION

The rapid proliferation of smart mobile devices including smartphones and tablets has significantly increased in recent years, primarily due to their support for a wide range of services that extend beyond conventional communication. These devices are equipped with advanced multimedia functionalities that greatly enrich user experience, particularly for Android users. Features such as high-resolution cameras and seamless content sharing capabilities enable swift transmission of multimedia data, including images and videos. The growing user interaction with these features has notably contributed to the widespread popularity of Android-based platforms, especially in emerging entertainment applications and development initiatives [1], [2]. Smart mobile devices typically connect through two primary wireless mediums: cellular networks, which provide services such as voice calls, messaging, and internet access; and Wi-Fi networks, which offer more economical internet connectivity compared to cellular data. The operation of these networks depends on substantial infrastructure, including access points and Base Stations (BSs), which facilitate device connectivity to broader network systems and the internet [3]. However, during catastrophic events such as wars, natural disasters, or terrorist attacks this infrastructure is often severely compromised, leading to major disruptions in communication. Rebuilding such infrastructure is a time-intensive process due to its inherent complexity. In these critical situations, establishing communication becomes essential for locating survivors and coordinating emergency response efforts. To address infrastructure breakdowns, Wireless Ad Hoc Networks (WANETs) is formed using mobile devices as network nodes that relay data packets to the nearest operational base station. Since individuals carrying these devices are likely to be mobile and evacuating affected zones, the MANET paradigm offers a more flexible and responsive solution under such dynamic conditions [4].

A MANET is a self-configuring wireless communication system that operates independently of fixed infrastructure. It consists of mobile nodes that frequently change their positions, reflecting the network's dynamic nature. These nodes, along with other devices in the environment, are capable of functioning without pre-established communication infrastructure. Communication within a MANET occurs either directly between nodes within transmission range or indirectly via intermediate nodes that forward messages. In both scenarios, nodes autonomously manage data transmission, thereby forming a decentralized wireless network characteristic of the MANET architecture, figure.1 [5].

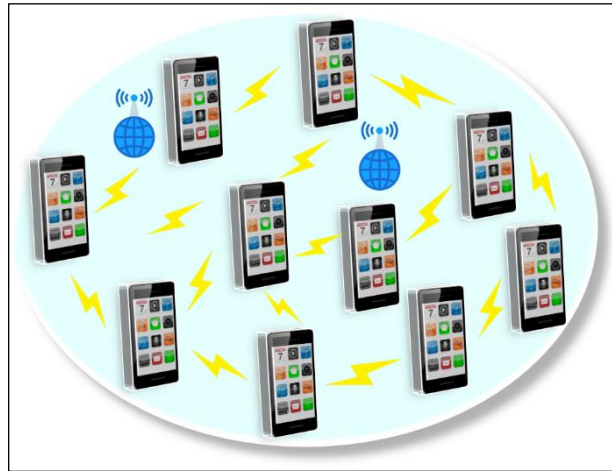


Figure 1: Ad hoc network of Android devices.

Source: Authors, (2026).

MANETs are applicable across various domains, including military operations, disaster recovery, and critical field missions. Their unique features such as dynamic topology, high mobility, limited bandwidth, and constrained energy resources distinguish them from conventional networks. The MANET ecosystem is rapidly evolving, with nodes frequently joining or leaving the network. Therefore, it is imperative to develop robust strategies that govern operational dynamics and address factors influencing network behaviour and performance [6]. The network data, such as traffic, node status, and topology, is extracted from android mobile nodes, thereby transforming it into tangible value, enabling for predictive analytics and adaptive modelling. Numerous data-driven methodologies have been explored in MANETs. By [7] have presented K-Nearest Neighbour for enhancing network performance in MANET environment. K-Nearest Neighbour (KNN) selects k nearest data points from the network to avoid packet loss and congestion. According to [8] have introduced Fuzzy Logic (FL) methodology for enhancing network quality in MANET. To construct MANET with enhanced QoS, FL is utilized that integrates FL rules, analyses packet scheduling system. In turn [9] have implemented Deep Q-Network (DQN) for establishing efficient QoS in MANET. The DQN selects optimal links with low delay and high stability for attaining an improved routing process. The conventional approaches are less efficient in dealing with fast network topology changes, node mobility, and link reliability. These methods generally do not perform well with energy-efficient routing, non-linear mobility model adaptability, and sustaining high PDR ratios in stressful situations [10].

1.1 OBJECTIVES OF THE WORK:

This research integrates a novel hybrid routing framework for MANETs, comprising DL and bio-inspired optimization approaches. The primary objectives are given below:

- ✓ To capture temporal patterns in node mobility, traffic dynamics, and link stability, an LSTM network is utilized.
- ✓ To extract spatial hierarchies and inter-node correlations within the network structure, a capsule network is employed.

This integrated framework facilitates context-aware decision-making, supports adaptive behaviour in complex wireless environments and enhances overall network performance in terms of QoS and automated functionalities. Given the volatile and unpredictable nature of MANET topologies, routing algorithms must be capable of rapid adaptation while efficiently utilizing computational and communication resources. However, several inherent challenges persist especially in achieving high throughput and discovering optimal multi-hop path [11]. Decentralized and self-organizing mobility of nodes often leads to unstable routing paths, making multi-objective routing a core challenge. This instability results in increased latency, inefficient energy consumption, and potential fragmentation of the network. Most of the difficulties encountered in MANETs are fundamentally linked to their highly dynamic topology [12]. Optimized Link State Routing (OLSR) protocol maintains current network topology information through periodic exchanges of control messages. It ensures route availability to neighbouring nodes when required, continually updates its routing data, and achieves control overhead reduction by selectively advertising only a subset of neighbouring nodes, thereby minimizing the rate of control packet dissemination [13]. Ad hoc On-Demand Distance Vector (AODV) protocol facilitates packet forwarding by serving as intermediate routers. In AODV, each node functions as a dynamic router, updating its local routing table only when a packet forwarding request is initiated or when the node itself originates the transmission [14]. Dynamic Source Routing (DSR) protocol is an effective reactive routing technique used in MANETS, which embeds the IP addresses of all intermediate nodes within the header of each data packet, enabling source-based routing. This header outlines the complete hop-by-hop path from source node to intended destination, ensuring precise route tracing throughout the transmission [15]. Destination Sequenced Distance-Vector (DSDV) routing protocol is labelled with sequence number, produced from destination node, and must be included in the sender's next routing update. For indicating a valid connection and odd when the route is considered broken [16].

Though these protocols enhance the availability of updated network topology, information at each node facilitate efficient route selection with minimal response time [17], [18]. The rapid adaptability comes at the cost of significant network bandwidth consumption, primarily due to the transmission of non-essential control packets required to maintain real-time topology awareness across all nodes. One of the most prominent strategies for designing in MANET routing protocols involves the use of bio-inspired algorithms. Ant Colony Optimization (ACO) based routing protocol learns activities of ants in identifying a path from the source of food to their colony. This behaviour of ants is utilized to solve shortest path routing problem [19]. Artificial Bee Colony (ABC) is a collective intelligence algorithm based on foraging behaviour of bees, developed for solving dynamic, time-varying and multi-objective problems in MANET routing strategy [20]. This research proposes a novel hybrid strategy for effectively routing the packets in MANETs. The contribution of the proposed routing approach in the MANET framework is listed below:

- The LSTM network is leveraged to model and predict the temporal variations in node mobility, traffic patterns, and link stability, thereby enabling more informed and predictive routing decisions.
- Capsule network is employed for capturing the spatial relationships among network nodes, enhancing node interactions and link dependencies for improved routing accuracy.
- Bonobo optimization algorithm is introduced, which applies cooperative and socially adaptive search strategies to optimally select the routing paths by balancing critical factors such as delay, energy consumption, mobility, link quality and metrics.

Organization: Section 2 delivers a brief proposed system explanation. Section 3 outlines system modelling implemented in research, while Section 4 discusses implementation, comparative analysis, and simulation outcomes. Lastly, Section 5 précises key outcomes and provides suggestions for future research directions.

II. PROPOSED SYSTEM DESCRIPTION

The proposed block diagram of CapsuLSTM optimized BOA configuration for MANET illustrated in figure.2, depicting the advanced topology that leverages DL models with bio-inspired optimization algorithms for robust MANET interactions.

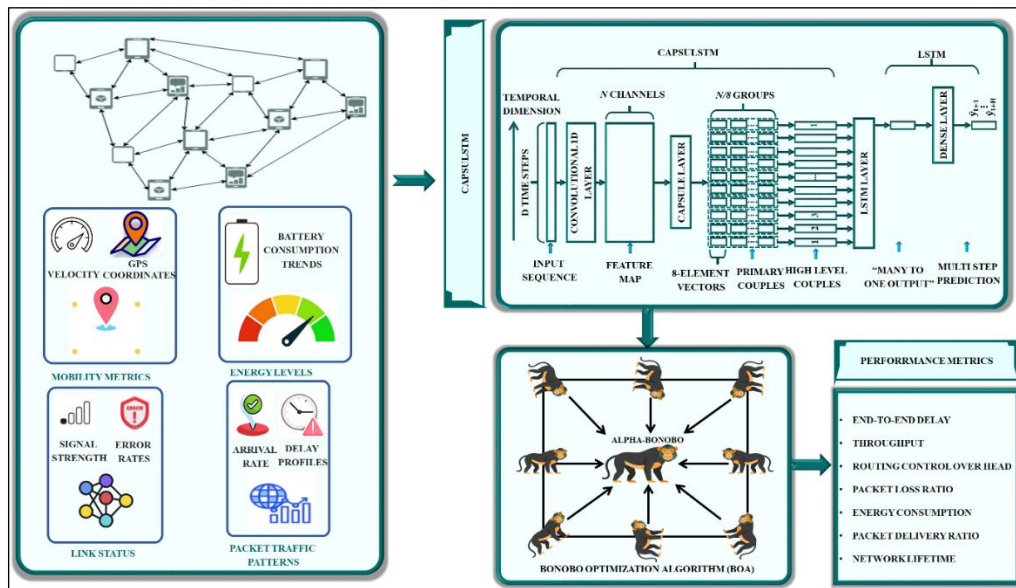


Figure 2: Proposed hybrid routing approach in MANET.

Source: Authors, (2026).

The real-time data are collected from each android-based mobile nodes that includes node mobility metrics, energy levels, link status, and traffic patterns. These parameters are given to the feature extraction module and updated on a regular basis for ensuring dynamic routing in MANET. The node mobility and network traffic data obtained are processed by LSTM network that captures historical patterns, where hidden state vectors encode time-dependent characteristics, crucial for route stability even under frequent node migrations. Capsule network captures high-spatial correlations from the network architecture, dynamic routing is encoded by vector norms, bridging gaps if the connection is lost or network topology is changed. The features extracted from both LSTM and capsule network is concatenated for attaining accurate routing paths. The merged feature routing space is then forwarded to the bonobo optimization algorithm, simulated by bonobo mating-cooperative behaviour accessing the network nodes and optimizes the routing paths in real-time.

III. PROPOSED SYSTEM MODELLING

III.1 CAPSULSTM

The proposed CapsuLSTM model is a hybrid DL framework, comprising capsule network and LSTM network, depicted in figure.3, process sequential routing data and predict future values. The capsule network integrates vector-based capsules effectively captures high-level spatial correlations in the dynamic MANET environment. LSTM module adopts temporal fluctuations in node mobility, link reliability and traffic behaviour by high-level capsules produced from the capsule network. The fully connected layers effectively converts the temporally encoded features into predictive outputs, demonstrating future routing metrics.

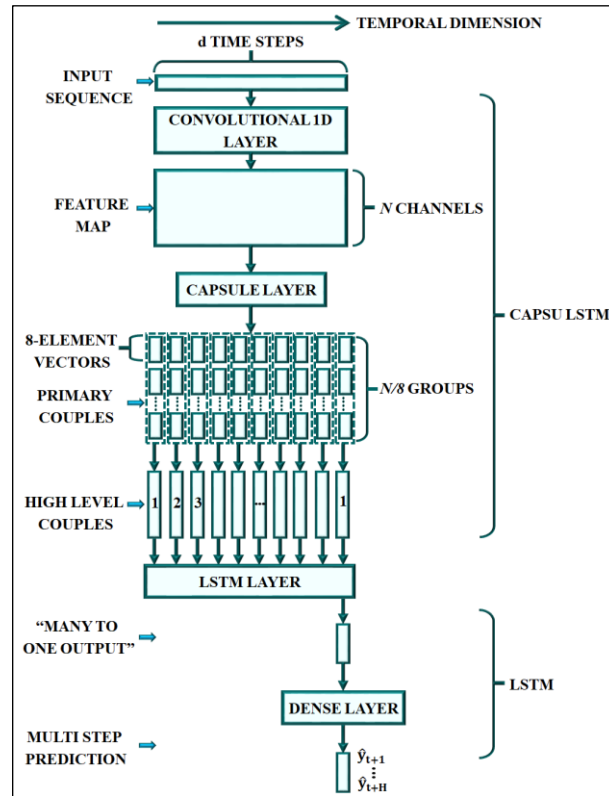


Figure 3: Architecture of CapsuLSTM model.

Source: Authors, (2026).

The core principle of capsule networks lies in their ability to capture and encode spatial dependencies such as scale, orientation, position, and relative positioning of attributes that are crucial in dynamic MANET environments, where node mobility and network topology frequently changes. The capsule structures effectively discern the behaviour of the packets which deviate from standard routing configurations, even an individual component is valid. As, the traditional CNN tends to overlook the spatial relationships between the node attributes, the capsule network, evaluates these features interact within the hierarchical structure, enabling more enhanced detection in routing, where packet sequences resemble legitimate traffic but deviate from expected spatial or temporal distribution. The capsule network decomposes their inputs such as node interactions and transmission events into essential components such as source ID, link status, demonstrating to produce structured representation of network event. The standard capsule network composed of three layers: Input, hidden and Output, specified in figure.4.

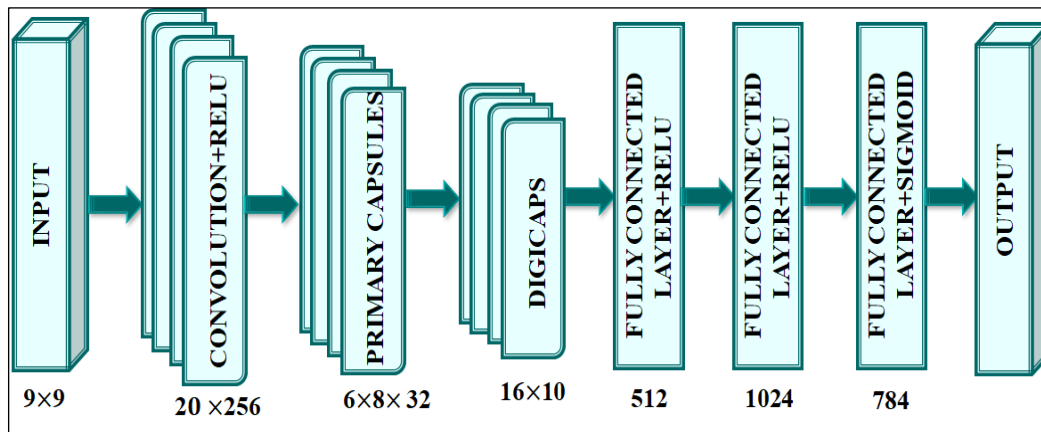


Figure 4: Structure of capsule network.

Source: Authors, (2026).

III.1.1 Input Layer:

This layer takes inputs such as raw packet data, node coordinates, or routing metrics.

III.1.2 Convolutional Feature Extraction Layer:

This layer contains 256 feature maps generated via 9×9 kernels and a stride of 1, using ReLU activation, which is ideal for filtering edge behaviours or localized traffic bursts.

III.1.3 Convolutional Capsule Layer:

The convolutional capsule layer is structured as $6 \times 6 \times 32$ capsules, each comprising eight convolutional units (9×9 kernel size, stride 2), effectively capturing movement patterns or localized node interactions.

III.1.4 Squashing Function:

The squashing function ensures that the vector outputs remain bounded between 0 and 1, preserving signal fidelity while preventing over activation in irregular routing events.

III.1.5 DigitCaps (Fully Connected Capsule Layer):

DigitCaps consists of ten capsules each with a 16D vector, acting as classifiers in routing states, anomaly levels, or traffic categories in MANET operations. CapsNets offer distinct improvements over CNN-based models in terms of resilience to adversarial perturbations, critical in MANETs where intrusion detection and secure routing are paramount. Subtle manipulations such as spoofed node identifiers or tampered packet headers evade CNN-based strategy but are more likely to be flagged by CapsNet due to its preservation of inter-feature spatial dependencies. The strength lies in its use of capsules aggregates of neurons encoding unified attributes, which function collectively to assess the integrity of network states. These capsules ensure that outputs stay consistent with underlying packet behaviour, rendering the model more robust against falsified input vectors common in adversarial routing attacks.

III.1.6 Mathematical modelling of Capsule Network:

The modelling of mathematical structure of the capsule network is crucial in transmitting and transforming feature informations across layers, thus preserving crucial spatial dependencies.

1. Convolutional Feature Extraction.

Activation at position (i, j) on k^{th} feature map is given by:

$$z_{i,j,k} = \sum_{l=1}^L W_{i,j,k,l} X_{i,j,l} + b_{i,j,k} \quad (1)$$

Where, output at position (i, j) for feature map k , is represented in local signal strength or traffic signature $(z_{i,j,k})$, the filter weight mapping from input channel l to output channel k is $(W_{i,j,k,l})$, input value at (i, j) in channel l is $(X_{i,j,l})$ and the bias term accounting for baseline activity is $b_{i,j,k}$. The equation (1) forms the first layer of feature abstraction interpreting node traffic volume or signal correlations.

2. Primary Capsule Layer.

The output vector of a capsule located at (i, j) in capsule k is computed as:

$$V_{i,j,k} = \text{Squash}(\sum_{l=1}^L W_{i,j,k,l} U_{i,j,l}) \quad (2)$$

Here, the capsule output $(V_{i,j,k})$ representing joint routing behaviour or mobility vector, the input feature from preceding capsules or convolutional units is $(U_{i,j,l})$ and the transformation matrix guiding feature mapping is $(W_{i,j,k,l})$, and *Squash* is the non-linear compression ensuring output vector length is constrained between 0 and 1. This step is crucial in ensuring that capsule vectors encode probabilistic yet bounded representations of localized MANET conditions.

3. Routing-by-Agreement Mechanism.

The higher-level capsules refine their inputs by computing agreement-weighted sums,

$$S_j = \sum_i c_{ij} \hat{u}_{ji} \quad (3)$$

The predicted output $(\hat{u}_{ji})$ from capsule i toward capsule j , potentially modeling transition behaviours between nodes. The coupling coefficient (c_{ij}) is the degree of influence of capsule i has on capsule j .

4. Final Capsule Output for Classification.

Final output for class k is computed by:

$$y_k = \text{squash}(s_k) \quad (4)$$

The input (s_k) is aggregated to capsule k , integrating multiple spatial features, *Squash* activation function normalizes vector magnitude for final interpretation such as classifying routing anomalies or behavioural states. Long Short-Term Memory unit is as essential unit in Recurrent Neural Networks (RNN) that is engineered for effectively model and capture temporal dependencies within sequential data. This capability is particularly characterize relevant variations in node mobility, link reliability, and traffic patterns in MANETs. The LSTM achieves this through a structured network of interlinked components designed to facilitate the selective retention and discarding of information over time. The standard LSTM cell architecture, illustrated in Figure.5, contains of three fundamental gates for control internal data flow. These gate mechanisms operate in conjunction with a memory cell that persistently updates and stores relevant data.

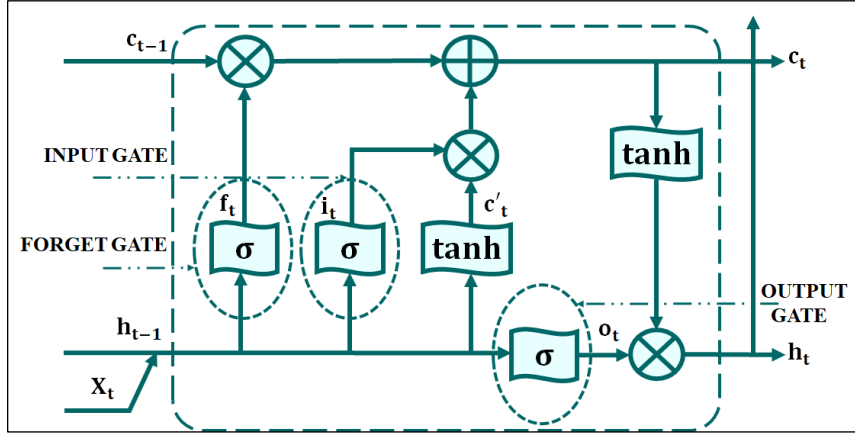


Figure 5: LSTM cell structure.

Source: Authors, (2026).

The LSTM networks applied to MANET dynamics, four gates collaboratively manage information propagation.

Input Gate: Input gate regulates significance of incoming data by applying a sigmoid activation to both current input and previous hidden state, thus selecting pertinent features for storage in memory cell.

Forget Gate: In contrast, the forget gate identifies which portions of previously stored information in the memory cell needs to be discarded, leveraging a sigmoid activation over the same input pair.

Memory Cell: The memory cell functions as a persistent data repository, receiving new candidate values from input gate and regulating memory content through forget gate's decision.

Output Gate: It regulates quantity of data extracted by memory cell for transmission to next hidden layer. It uses a sigmoid activation to make the gating decision and applies an $\tanh$ activation to normalize the output within the range of -1 to 1 .

Together, these gates enable the LSTM unit to effectively capture and utilize temporal fluctuations in MANET environments. With its unique composition dedicated memory cells and gate-regulated information pathways, the LSTM excels in modelling long-range dependencies inherent in dynamic network scenarios.

III.1.7 Mathematical Modelling of LSTM cell:

At each time step t , the internal operations of LSTM cell are governed by a series of equations that define the behaviour of its core memory mechanisms and three crucial gates. It control selective retention, modification, and transmission of information, enabling cell to maintain and update its state effectively across time. Forget gate determines which components of previous hidden state (h_{t-1}) and current input (x_t) needs to be retained or discarded. This decision is made by applying a sigmoid activation function (σ) to weighted sum of these inputs, as defined in Equation (5):

$$f(t) = \sigma\{W_f(h_{t-1}, x_t)\} \quad (5)$$

Where, σ is sigmoid activation function, W_f represents forget gate's weight matrix, h_{t-1} is hidden state from previous time step, x_t denotes input at current time step. Input gate regulates that components of new information needs to be integrated into current cell state (f_t). This consists of:

1. An input gate layers, integrating sigmoid function for choosing the values for updating.
2. A $\tanh$ layer generates new candidate values (C'_t) for possible inclusion into the cell state.

These are mathematically described by input gate's parameters,

$$I_t = \sigma\{W_i(h_{t-1}, x_t)\} \quad (6)$$

$$C'_t = \tanh\{W_c^*(h_{t-1}, x_t)\} \quad (7)$$

Updated cell state (C_t) is computed by combining contribution from previous cell state (C_{t-1}) modulated by forget gate output (f_t), with candidate cell state (C'_t) influenced by input gate (I_t). This update operation is given by Equation (8):

$$C_t = (f_t * C_{t-1}) + I_t * C'_t \quad (8)$$

Output gate evaluates number of updated cell state is passed to hidden state. After applying sigmoid activation, the output is scaled by a $\tanh$ transformation of cell state, resulting in final hidden state h_t .

$$O_t = \sigma\{W_o(h_{t-1}, x_t)\} \quad (9)$$

$$h_t = O_t * \tanh(C_t) \quad (10)$$

The recurrent weight matrices (W_f, W_i, W_c, W_o) encode the internal memory structure and capture the temporal relationships across time steps. At each step (t), these equations govern the dynamic interactions between current input (x_t), hidden state (h_t) and cell state (C_t). Previous values are denoted by (h_{t-1}) and (C_{t-1}), forming previous time step $t - 1$ for each update. σ represents sigmoid activation, (f_t), (i_t) and (o_t) correspond to forget, input, and output gates respectively, (C_t') signifies candidate state, (C_t) and (h_t) define the updated memory and hidden states. Collectively, these expressions elucidate how the LSTM structure efficiently manages information over time, a capability that is central to modelling sequential dependencies in neural networks. This LSTM framework is highly efficient in analyzing temporal dynamics in MANETs, where node mobility, link reliability, and traffic patterns exhibit significant variability. The integration of Capsule network and LSTM model, significantly learns structural and temporal dependencies facilitating smart routing decisions based on dynamic network conditions.

III.2 BONOBO OPTIMIZATION ALGORITHM

BOA is a metaheuristic technique that is inspired by the unique reproductive pattern and co-operative behaviour of bonobo communities. The BOA approach mimics the bonobos' fission–fusion dynamics, where individuals split into smaller, resource-seeking groups during the day and reunite at night, enhancing exploration and intensifying search diversity, as illustrated in Figure 6. This biological correlation enriches BOA's search dynamics, allowing adaptive routing in highly dynamic MANET environments.

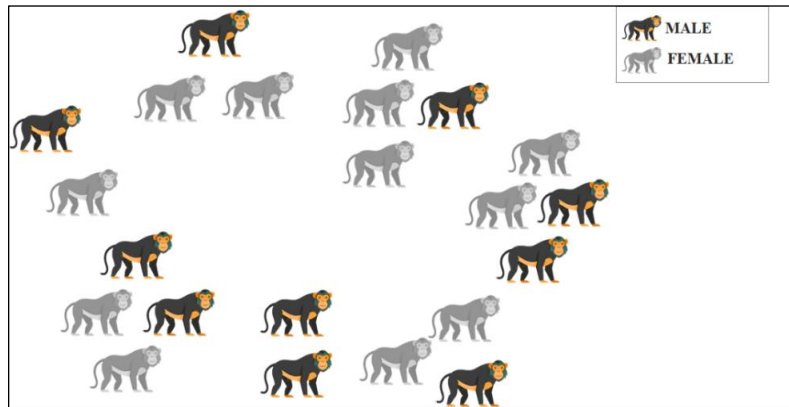


Figure 6: Bonobo social groups (Fission and Fusion).

Source: Authors, (2026).

This biological correlation enriches BOA's search dynamics, allowing adaptive routing in highly dynamic MANET environments. This informed mechanism incorporates each routing candidate in the population is represented as bonobo agent. Each bonobo interacts based on its phase probability, navigating either a positive phase (pp), which emphasizes diversity and widespread search, or a negative phase (np), which tightens selection pressure. These phases are quantified by positive phase count (ppc) and negative phase count (npc), reflecting duration of each behavioural mode across iterations. The visual differentiation between male and female bonobo is indicated as dark and light entities, given in figure.7, signifies their role in the optimizer's strategy. Bonobo with highest fitness in dominance hierarchy is termed the alpha bonobo, serving as a guide for the population's convergence.

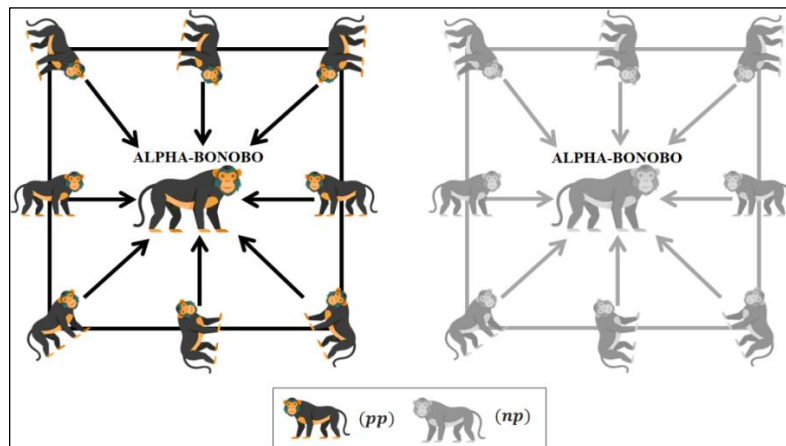


Figure 7: Bonobo's movement directions with higher probabilities.

Source: Authors, (2026).

In BOA's population structure, agents are ranked by fitness, defined here as the efficiency of proposed routes and the highest-ranking agent is deemed the alpha bonobo. Routing optimization occurs through four biologically-inspired mating approaches. Bonobo optimization algorithm adapts its mating strategies based on the network's behavioural phase classified as positive or negative to enhance routing performance in MANETs. During the positive phase (pp), analogous to a well-resourced and stable bonobo community, the environment exhibits favourable communication conditions such as high node connectivity, reliable link quality, minimal congestion, and efficient packet delivery. Under this phase, two primary mating-inspired routing mechanisms dominate:

- ❖ Promiscuous routing interaction, allowing broad link formation between dominant and subdominant nodes, fostering route diversity.
- ❖ Restrictive routing exchange, where only high-ranking nodes (those with optimal routing metrics) participate in route propagation, enhancing stability and minimizing overhead.

Here, oestrus females are characteristically represented by available routing options, accessible to all node ranks in promiscuous behaviour but reserved for elite node interactions in restrictive behaviour. As conditions decline and the network enters the negative phase (np) reflecting resource scarcity or routing instability, the optimizer shifts to more selective exploration tactics:

- ❖ Consortship routing, representing node pairs that temporarily isolate from the network cluster to refine route decisions. These isolated evaluations converge back into the main topology once refined paths are established.
- ❖ Extra-group routing, following external link exploration where nodes connect across fragmented network regions. Though less frequent, this behaviour introduces new routing paths, useful in partitioned MANETs or during topology reformation.

These biologically modelled strategies are mathematically formulated within BOA to iteratively evolve routing paths. The resulting algorithmic logic, structured in the BOA flowchart, Figure.8, captures the full spectrum of social-inspired phases to guide dynamic peer-to-peer communication in MANETs.

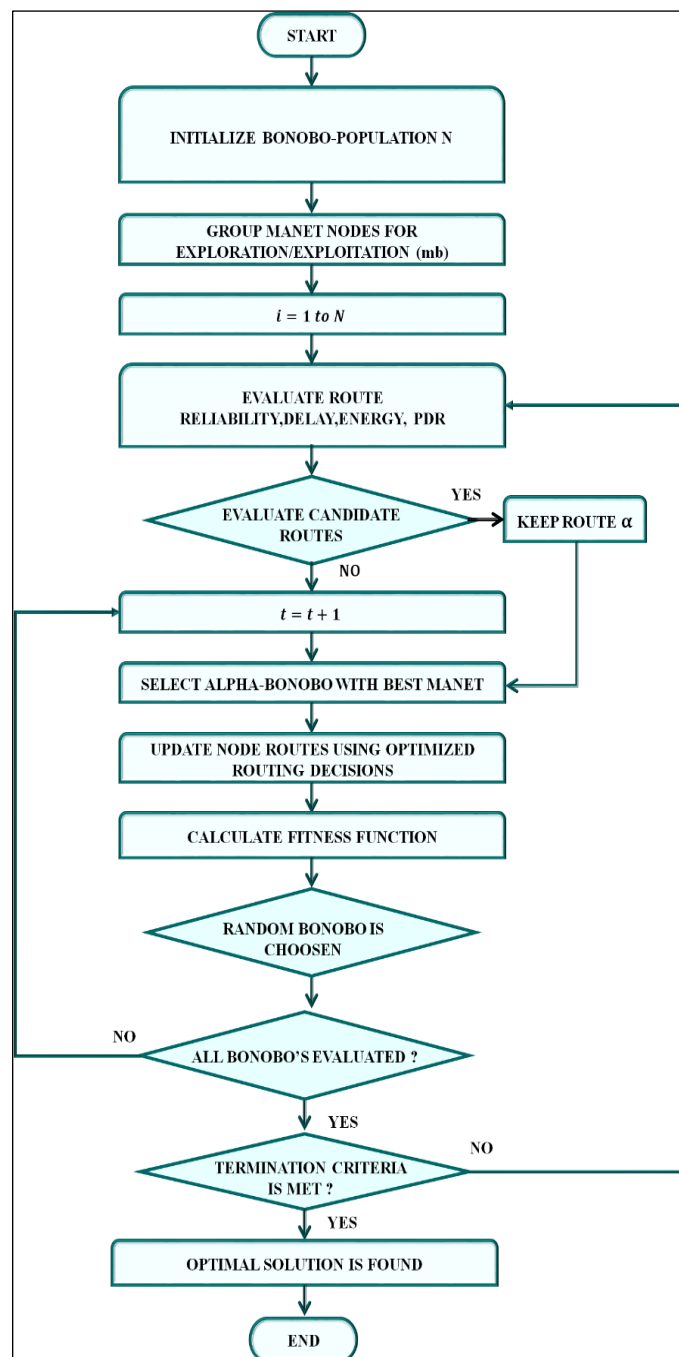


Figure 8: Flowchart of BOA.
Source: Authors, (2026).

III.2.1 Inclusive and Exclusive Mating Practices:

Mating strategy in BOA is directed by phase probability parameter (pp), which influences likelihood of generating new candidate solutions. Initially set to 0.5 pp is dynamically adjusted in each iteration to adapt exploration intensity. When a randomly generated scalar r in $[0, 1]$ is less than or equal to (pp), new bonobo (candidate route solution) is generated using:

$$n_{b_j} = b_j^i + r_1 s^a (\alpha_j^b - b_j^i) + (1 - r_1) s^s flag(b_j^i - b_j^p) \quad (11)$$

Where, b is the bonobo (candidate solution vector), n_{b_j} is the offspring generated over for the j^{th} variable, b_j^i and b_j^p are the existing and reference bonobo variable values, r_1 is randomly distributed value between 0 and 1, s is the interaction strength sharing coefficients, $flag$ argument in $[-1, 1]$, binary flag controlling mating mode. If the present bonobo i^{th} produces a better routing performance than the reference bonobo p^{th} the mating is classified as promiscuous, setting the $flag$ to 1. This emphasizes exploration and encourages diversity among route candidates. Otherwise, if the reference bonobo is more optimal, the same process is applied but as restrictive mating, maintaining convergence by preferred elite solutions.

III.2.2 Partnership and Mating Strategies Beyond Group:

Mating behaviour is then diversified using extra-group mating and consortship approaches, which are controlled by the mating phase parameter (pp).

$$n_{b_j} = \begin{cases} b_i^j + e^{(r_3^2 + r_3 - 2r_3^{-1})} (Var_{max_j} - b_j^i), & \alpha_j^{bonobo} \geq b_j^i \\ b_i^j - e^{(-r_4^2 + 2r_4 - 2r_4^{-1})} (b_j^i - Var_{min_j}), & r_3 \leq p_d \\ b_i^j - e^{(r_3^2 + r_3 - 2r_3^{-1})} (b_j^i - Var_{min_j}), & \alpha_j^{bonobo} \leq b_j^i \\ b_i^j + e^{(-r_4^2 + 2r_4 - 2r_4^{-1})} (Var_{max_j} - b_j^i), & r_3 \geq p_d \end{cases} \quad (12)$$

The phase dynamic parameter (p_d), initially set to 0.5, is adaptively updated according to the evolutionary progress of the optimization process. This parameter fine-tunes the search mechanism to effectively identify optimal solutions. For each decision variable j , lower and upper bounds are signified by Var_{min_j} and Var_{max_j} , respectively. When the randomly generated value r_2 exceeds extra-group mating probability p_{xgm} , a new offspring is generated using consortship mating approach defined as:

$$n_{b_j} = \begin{cases} n_{b_j} + e^{r_s} flag(1 + r_1)(b_j^i - b_j^p), & r_6 \leq p_d \\ b_j^p, & otherwise \end{cases} \quad (13)$$

Here, (r_1, r_2, r_3) represent random variables that are uniformly distributed within interval $[0, 1]$. Thus, the hybrid framework combines the time modelling prowess of LSTM, hierarchical spatial representation of Capsule Networks, and biologically inspired adaptability of the BOA for facilitate intelligent decentralized routing in MANETs.

IV. RESULT AND DISCUSSION

This proposed hybrid routing protocol comprising of hybrid DL model and bio-inspired optimization algorithms attains optimal routing path for MANET environment. The developed method is evaluated and the simulation parameters are given in table.1. Performance metrics involves number of nodes, PDR, packet loss ratio, throughput, delay, routing control overhead, energy usage and network lifetime for efficiently managing data transmission.

Table 1: Parameter Specifications.

Parameters	Values
Packet size	512 bytes
Number of nodes	20 to 80
Speed of the node	5-20 m/s
Node assignment	Random distribution
Area of simulation	1000 m × 1000m
Simulation time	1000 s
Traffic category	Constant Bit Rate (CBR)
Wireless range of transmission	250 meters
Protocol used for routing	BOA
Mobility model	Random waypoint
Pause time (s)	10 s

Source: Authors, (2026).

IV.1 END-TO-END DELAY

E2E delay is time required for an unloaded data packet to come in that successfully traverse since alone location to a new.

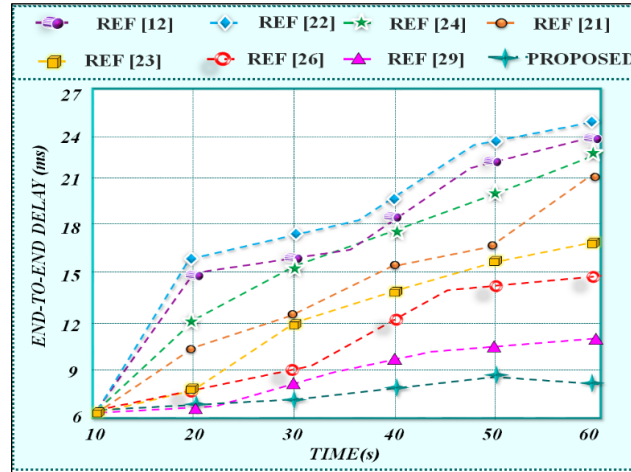


Figure 9: End to End delay Vs Time (ms).

Source: Authors, (2026).

Figure. 9 presents comparative analysis of end-to-end delay performance across various routing protocols in MANET environment. The proposed hybrid CapsuLSTM–bonobo optimization algorithm exhibits the lowest delay throughout all time intervals, reliably outperforming other protocols, ensuring efficient delay minimization strategy for routing in dynamic MANET scenarios. Forest Boost Regression-Artificial Neural Network (ANN) [21] and ANN- Glow Worm Optimization (GWO) [22], indicating moderate delay levels and routing approaches like QoS-based Dynamic Secured Broker Selection Architecture (QoS-DSBS) [23], QoS- aware and Social-aware Multimetric Routing (QSMVM) [24], Cross-layer Adaptive Fuzzy-based Ad-hoc On-Demand Distance Vector routing protocol (CLAF-AODV) [25], Improved Priority Aware mechanism AODV (IPA-AODV) [22], and Cascading Back Propagation Neural Network (CBPNN) [12] demonstrates relatively higher delay curves, indicating reduced efficiency.

IV.2 THROUGHPUT

Amount of data successfully transmitted over network per unit time, is termed as throughput, which is measured in kbps. Throughput reflects network's capacity for handling network traffic efficiently under varying node densities.

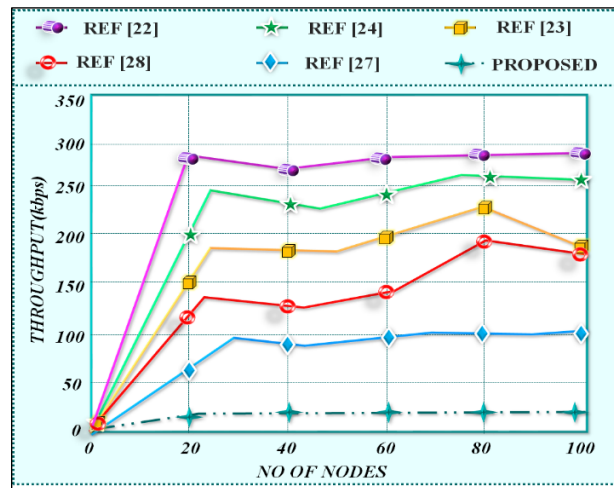


Figure 10: Throughput (kbps) Vs Number of nodes.

Source: Authors, (2026).

Figure.10 represents performance analysis of throughput metrics across several MANET routing protocols with varying node densities. Across increasing node densities, the highest throughput is attained by the proposed CapsuLSTM–BOA approach, outperforming all other protocols. Hybrid Dual Optimization ML model (HDOMLM) [26] and PSO [27] follow with declining performance. QoS-DSBS [23] and CLAF-AODV [25] offer moderate throughput, while IPA-AODV [28] records the lowest efficiency, validating the efficiency of routing strategies in MANET environment.

IV.3 ROUTING CONTROL OVERHEAD

The excess bandwidth consumed while routing data during communication, is quantified by routing control overhead. The lower the overhead, more efficient the network operation is.

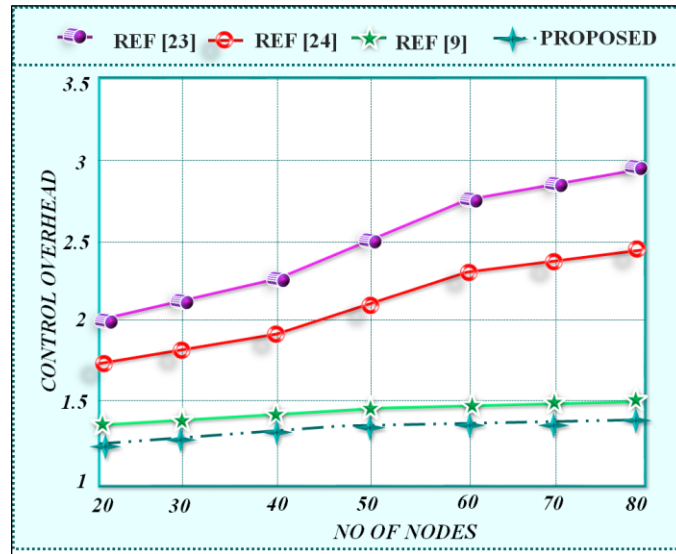


Figure 11: Routing control overhead Vs Number of nodes.
Source: Authors, (2026).

Figure.11 illustrates comparative analysis of control overhead incurred by various MANET routing protocols as node density increases. Number of nodes ranging from 20 to 80, while routing control overhead, measured between approximately 1.0 and 3.5 units. Five routing strategies are depicted, the proposed CapsuLSTM BOA, DQN [9], CLAF-AODV [25], and QoS-DSBS [23]. The proposed CapsuLSTM-BOA model determines the most efficient performance, maintaining the lowest control overhead throughout all node counts.

IV.4 PACKET LOSS RATIO

The proportion of number of data packets failed to reach destination to total number of packets sent is packet loss ratio. The reduced packet loss exhibits improved network reliability.

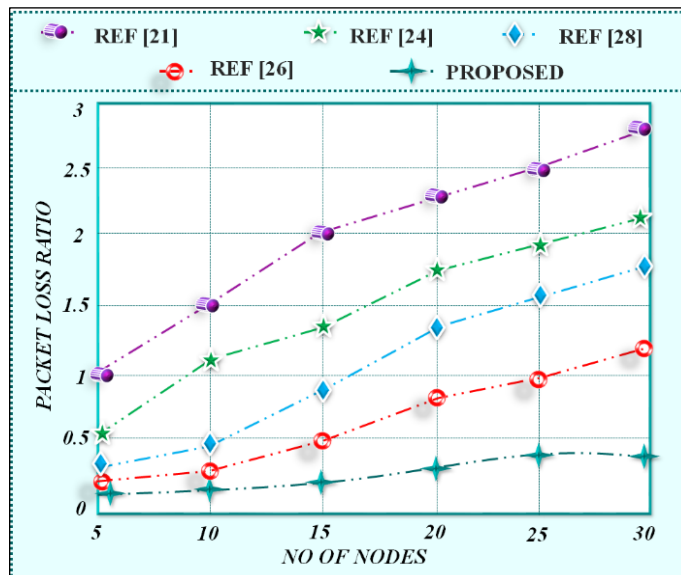


Figure 12: Packet loss ratio Vs Number of nodes.
Source: Authors, (2026).

Figure.12 visualizes the packet loss ratios across increasing node counts for multiple MANET routing protocols. The proposed capsule network with LSTM optimized BOA consistently maintains the lowest packet loss, showcasing superior reliability. ANN-GWO [22] and PSO [27] follow with moderately efficient performance, while CLAF-AODV [25] and QSMVM [24] exhibit higher loss rates, especially as network density grows. This performance analysis confirms BOA's enhanced stability and adaptability in dynamic MANET environments, with improved packet delivery efficiency among the compared routing strategies.

IV.5 ENERGY CONSUMPTION

Energy usage is total of energy network nodes used during scenario. This is achieved through measuring energy level of each individual node during end of trial and accounting for its residual energy.

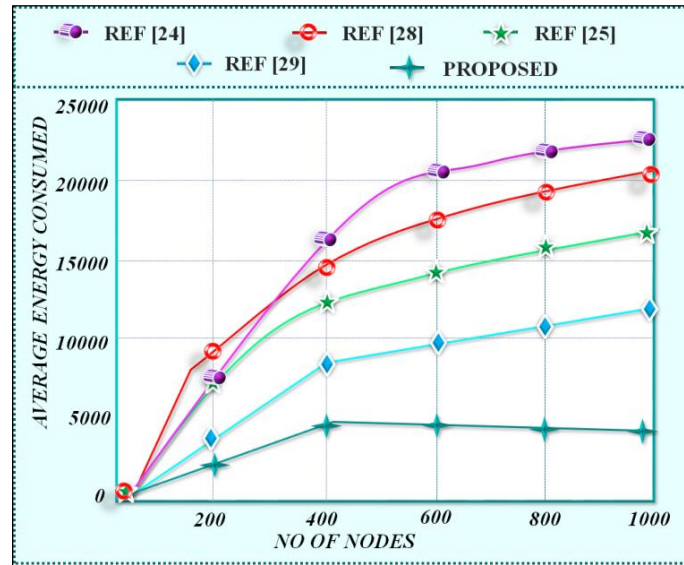


Figure 13: Energy consumption Vs Number of nodes.
Source: Authors, (2026).

Figure. 13 displays average energy consumed by various routing protocols in relation to number of nodes in a network, highlighting their efficiency in energy consumption. With an increase in number of nodes, overall energy consumption tends to go up for all protocols. From the figure, the proposed CapsuLSTM-bonobo optimization algorithm have the lowest average energy consumption throughout the number of nodes, pointing towards greater energy efficiency than the other routing protocols such as CLAF-AODV [25], ML-Fresh [29], PSO [27], Forest Boost Regression-ANN [21].

IV.6 PACKET DELIVERY RATIO

Ratio of number of packets delivered by upper layers compared to number of packets which came into destination is referred to as PDR. This standard represents degree of proposed way from a sending point toward a target.

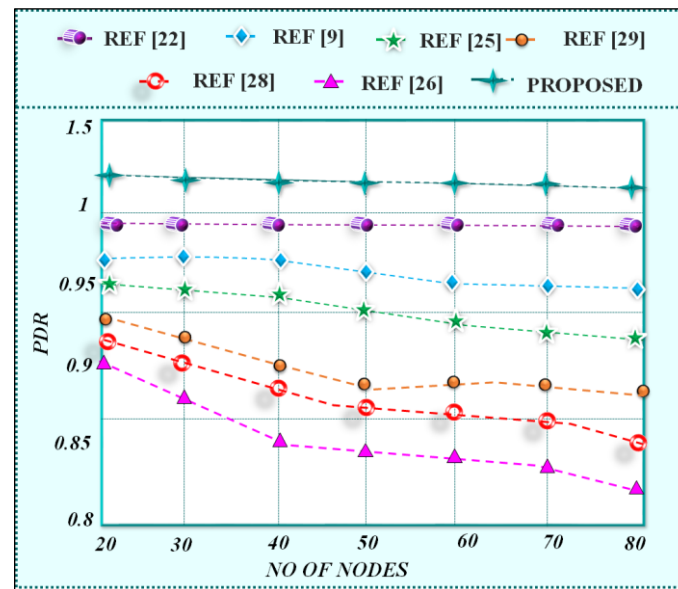


Figure 14: PDR Ratio Vs Number of nodes.
Source: Authors, (2026).

Figure.14 shows PDR performance of multiple routing methods as node count increases. The proposed CapsuLSTM with BOA consistently delivers the highest PDR across all node densities, highlighting its exceptional efficiency. The conventional routing protocols such as IPA-AODV [28] and ML-Fresh [29] maintain relatively higher PDR than DQN [9], forest boost regression-ANN [21], PSO [27], and ANN-GWO [22].

IV.7 NETWORK LIFETIME

The total operational time before network becomes inoperative because of depletion of nodes, network lifetime is a crucial for assessing energy efficiency.

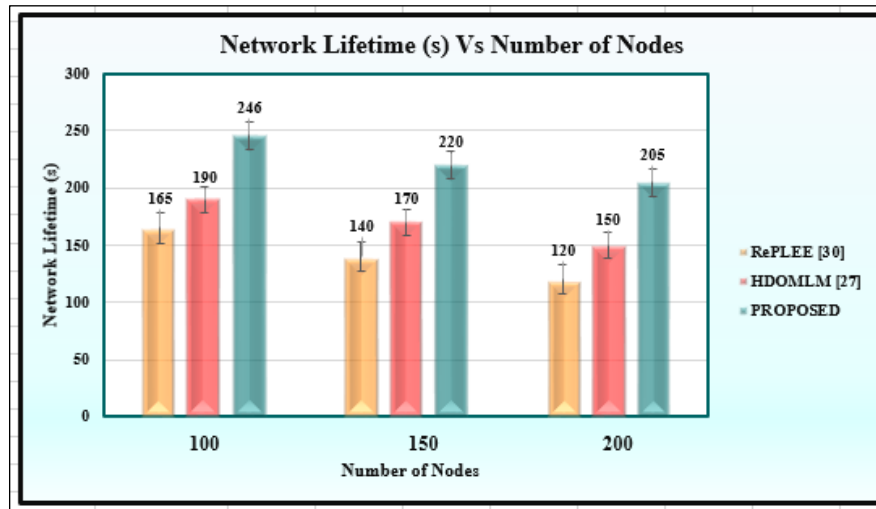


Figure 15: Network lifetime Vs Number of nodes.

Source: Authors, (2026).

Figure.15 demonstrates a performance analysis of network life time with different node densities, comparing three different routing protocols such as Replacing Relay Nodes to Prolong Lifetime and improve Energy Efficiency (RePLEE) model [30], HDOMLM [26] and the proposed CapsuLSTM optimized BOA routing approach. From the figure, the proposed approach consistently achieves the longest network lifetime at all node densities, demonstrating superior energy efficiency and robust scalability. Whereas the conventional approaches offering substantial lifetime but showing a steeper decline with increased nodes compared to proposed approach, confirming effectiveness in prolonging network longevity in MANETs through its integrated deep learning and bio-inspired optimization approach, proving most efficient and adaptable.

V. CONCLUSION

This paper introduces a hybrid routing paradigm for MANETs, integrating temporal and spatial learning through techniques like LSTM and Capsule Networks, with the BOA framework. The LSTM approach effectively captures temporal fluctuations, long range dependencies are modelled, inheriting dynamic mobility patterns to decentralized network. Capsule network significantly preserves spatial relationships, retaining contextual distinction in link stability and node behaviour. The Bio-inspired algorithm BOA dynamically selecting optimal routing paths through swarm intelligence principles, even under high node mobility and environmental uncertainty. Effectiveness of introduced routing approach, is validated, a comprehensive performance evaluation is conducted by comparing against existing approaches. From the outcomes, the proposed technique enables real-time, adaptive peer-to-peer communication and robust path selection amidst fluctuating mobility and link quality, thereby improving overall network resilience and data throughput.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Kannaki, S. Malathy.

Methodology: Kannaki, S. Malathy.

Investigation: Kannaki, S. Malathy.

Discussion of results: Kannaki, S. Malathy.

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Writing – Review and Editing: Kannaki, S. Malathy.

Resources: S. Malathy.

Supervision: S. Malathy.

Approval of the final text: Kannaki, S. Malathy.

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