International Journal of Advanced Trends in Engineering and Management
(ISSN 2583-7052)

Vol. V, No. 05, pp. 30-37, May

Intelligent Energy-Efficient MANET Clustering Using Artificial Rabbits Optimization and Graph Transformer Network

E. Immanuvel Bright[3]

[3]Department of Electrical and Electronics Engineering, Erode Sengunthar Engineering College, Perundurai, Erode, Tamil Nadu, India - 638057.

Corresponding Author E-mail

ABSTRACT: Routing challenges in Mobile Ad Hoc Networks (MANETs) are caused by node mobility, limited energy, unstable links and congestion. This work proposes an intelligent routing framework based on ARO-GTN for reliable and energy-efficient communication. Network parameters, such as residual energy, node degree, neighbour distance, mobility, and link quality are collected to characterize the network conditions. The Artificial Rabbits Optimization (ARO) algorithm selects the best cluster heads and creates stable clusters by efficiently exploring and exploiting. Then a Graph Transformer Network (GTN) is applied to model network relationships and predict suitable routing paths using attention based learning. The proposed routing mechanism provides energy aware path selection, congestion avoidance and efficient packet forwarding. The simulation results show that the proposed ARO-GTN allows routing based on energy aware and congestion avoidance. It achieves 83 kbps throughput, 60 J energy consumption, 83% PDR, 60 ms delay and 83 s network lifetime at 100 nodes, showing better network performance.

Keywords: MANET, ARO, GTN, Intelligent Routing, Cluster Head Selection.

1. Introduction

MANETs are self-forming and self-organizing networks of mobile devices without any infrastructure, which enables these networks to configured for communications in a dynamic manner by the mobile devices themselves [1]. Because of these characteristics, MANETs find widespread use in applications ranging from monitoring the environment and emergency situations to military operations, disaster control, and industrial communications. The decentralized nature of MANETs allows for the possibility of communication in situations where normal network infrastructure is unavailable or difficult to set up [2].

On the other hand, performance of the MANETs is greatly influenced by the mobility of the nodes and lack of computational and energy resources. Since mobile nodes keep on changing positions, there is a frequent variation in the topology and connectivity among the nodes. Moreover, due to limitations in terms of battery power, computing, and memory, it is necessary to use available resources efficiently while collecting and transmitting data. The mobility of nodes causes unexpected breaks in the established link or creation of a new link, thus making it difficult to establish routes [3].

Several traditional optimization methods have been used to improve clustering head and routing optimization in MANET. ACO is used for cluster head selection and path selection which utilizes pheromone based searching; but re-computations of pheromone again add some computational complexity. GWO offers an effective population based method that selects appropriate cluster heads based on node energy, connectivity, and other fitness attributes; but exploitation power of GWO limit search space in difficult optimization cases. ABC makes use of foraging strategy of honey bees for cluster head selection and energy aware clustering; but more iteration counts needed to get stable results [4-6]. The need for these shortcomings led to the development of ARO for efficient clustering head selection in order to offer better trade-off between exploration and exploitation.

Routing protocols are used to enhance communication in MANET. One of these protocols is Ad-hoc On-Demand Distance Vector (AODV) which establishes routes when needed but creates high control overhead when the topology of network frequently changes. Another routing protocol is Dynamic Source Routing (DSR) which uses source and packet caching. However, this protocol has high packet overhead because long routes use long header lengths. Optimized Link State Routing (OLSR) reducing routing overhead by using multiple points of relay but requires regular topology update regularly [7-9]. Therefore, it leads to motivation to propose GTN as the optimal approach for adaptive, reliable, and energy-efficient route finding.

1.1 Research Gap

Existing clustering and routing methods suffer from limitations such as computational complexity, increased iteration, routing overhead, and frequent topology updates in dynamic MANETs. Moreover, most of the existing methods do not jointly optimize the cluster-head selection and the intelligent route prediction. Hence, this work combines ARO for robust and power-saving clustering and GTN for adaptive route prediction to satisfy the requirement of reliable and efficient MANET communication.

2. Recent Works

S. No	Tittle/ author name/year	Methodology used	Advantages	Disadvantages
1.	Yilmaz *et al* (2025) [10]	Uses hybrid adaptive clustering with energy, mobility, connectivity and distance parameters and DSDV for routing-table based communication.	Enhances the cluster stability, energy efficiency, network lifetime and reliable routing employing adaptive clustering and loop free DSDV routes.	In highly dynamic networks, frequent cluster changes and DSDV routing-table updates increase the control overhead and energy consumption.
2.	Goswami *et al* (2025) [11]	Uses a multi-objective function including energy consumption, hop count, and link quality and path reliability. With TORA, Fused LSO-DOA gives the optimal and reliable path selection.	Enhances energy efficiency, path stability, route reliability and network lifetime in dynamic MANETs.	The joint optimization and TORA increase the routing overhead and the computational complexity, especially in highly dynamic networks.
3.	Kumar *et al* (2023) [12]	Uses a Modified Whale Optimization Algorithm (MWOA) for efficient cluster-head selection and secure routing based on energy, distance and node based parameters.	The clustering efficiency, routing security, energy consumption and network lifetime are improved by selection of appropriate cluster heads and safe communication paths.	The modified optimization process result in higher computation complexity and longer convergence time, particularly for large and dynamic MANETs.
4.	Rohini *et al* (2023) [13]	Uses Firefly Algorithm (FA) to select optimal cluster heads based on Residual energy, Distance, Connectivity and Node Fitness The selected cluster heads form energy efficient clusters for MANET communication	Balances the clustering process for better energy utilization, cluster head selection, network lifetime and communication efficiency.	The Firefly based optimization might need more computational effort and iterations to converge, especially in large and highly dynamic MANETs.

2.1 Objectives

- To perform efficient network analysis, it is required to gather essential MANET network information such as residual energy, node degree, neighbour distance, mobility speed and link quality.
- To enhance energy utilization and cluster stability by optimizing cluster head selection with the ARO algorithm.
- To develop an efficient graph representation based on the GTN to extract neighbourhood features efficiently and predict route intelligence.
- To design an intelligent routing mechanism based on best path selection, energy aware forwarding and congestion avoidance for reliable data transmission.

3. Proposed Work Explanation

The proposed system starts with the MANET environment, where the mobile nodes communicate with each other through the dynamic wireless links. The network information collection block collects important parameters such as residual energy, node degree, distance to neighbouring nodes, mobility speed and link quality. These parameters are inputted to the ARO algorithm for fitness evaluation, exploration and exploitation to obtain the optimal cluster heads. The optimized results indicate that the cluster formation process performs cluster head election, cluster member assignment and cluster maintenance to enhance the cluster stability and efficient utilization of network resources.

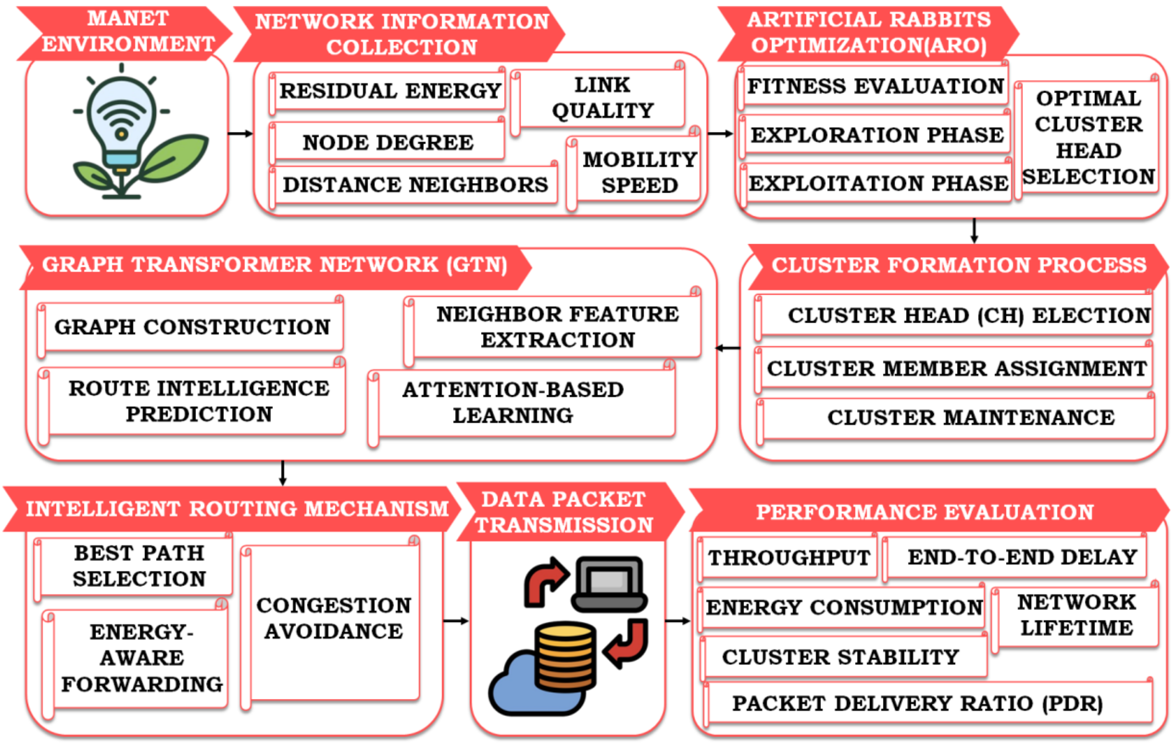

Figure 1: *proposed system Architecture*

The GTN constructs the network graph after the formation of clusters, and extracts the neighbourhood features to learn relationships among mobile nodes. It uses an attention-based learning mechanism to predict the route intelligence which is used by the intelligent routing mechanism to select the best path, forward in an energy-aware fashion and avoid congestion. The chosen protocol is used to transfer data packets between nodes of the network. The proposed system is evaluated using throughput, end-to-end delay, energy consumption, network lifetime, cluster stability and PDR to evaluate the efficiency of the proposed ARO-GTN based routing approach.

4. Proposed System Modelling

4.1 Network Information Collection

The MANET network is made up of mobile nodes which keep exchanging information as their locations and connectivity keep varying. In the course of operation of the network, each individual node offers important information regarding residual energy, node degree, neighbour distance, mobility speed, and link quality. Residual energy refers to the energy level of the battery, node degree is the number of neighbours that a node has, and neighbour distance is the communication distance among neighbouring nodes. On the other hand, mobility speed is concerned with the mobility of nodes, and link quality refers to communication links reliability. This information is kept updated from time to time depending on node mobility, energy level, and connectivity. It is then used as input in the ARO algorithm for proper cluster-heads' selection.

4.2 ARO

The ARO algorithm is based on the foraging and hiding behaviours of rabbits for cluster-head optimization. A fitness function evaluates candidate nodes according to residual energy, node degree, distance, mobility speed, and link quality. ARO searches and optimize the candidate solutions. The node with the best fitness is selected as the cluster head for stable and energy-efficient clustering.

The candidate cluster-head solutions are the initial population of artificial rabbits. Each rabbit is randomly initialized within the predefined search bounds as

$$z_{i,k} = r(ub_k - lb_k) + lb_k, \quad k=1, 2, d$$

Where $z_{i,k}$ is the position of i^{th} rabbit, ub_k and lb_k are the upper and lower bounds, d is the number of decision variables and r is a random number between 0 and 1.

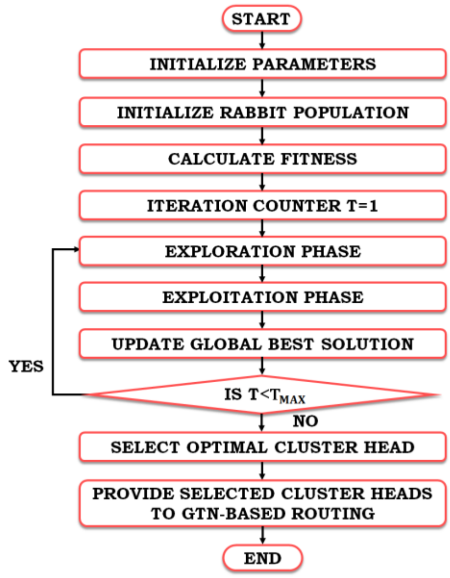

Figure 2: *Flowchart of ARO*

The fitness function evaluates the cluster-head candidates based on energy, connectivity, distance, mobility and link quality. The cluster head is chosen by the best fitness of the candidate:

$$F = w_1(1 - E_i^{norm}) + w_2(1 - D_i^{norm}) + w_3 d_i^{norm} + w_4 v_i^{norm} + w_5(1 - LQ_i^{norm}) \quad (1)$$

Where E_i^{norm}, D_i^{norm}, d_i^{norm}, v_i^{norm} and LQ_i^{norm} are normalized residual energy, node degree, distance, mobility speed and link quality respectively.

In the exploration phase ARO explores different regions of the solution space by using the detour-foraging behaviour of rabbits:

$$v_i(t+1) = z_j(t) + R\left(z_i(t) - z_j(t)\right) + round(0.5r_1)n_1 \quad (2)$$

Where $z_i(t)$ is the current rabbit position, $z_j(t)$ is a randomly selected rabbit, R controls the search movement, and n is a random number in the range of 1~N (0, 1). The coefficient of exploration is given by

$$R = lC \quad (3)$$

Where l is the search step and C is a randomly generated binary vector. This mechanism enables ARO to search different cluster-head combinations, and avoids premature convergence.

In the exploitation phase, ARO uses the random hiding behaviour of rabbits to improve promising solutions. The burrow position is generated as,

$$b_{i,j}(t) = z_i(t) + Hgz_i(t) \tag{4}$$

Where H is hiding coefficient and g is a randomly chosen dimension vector. The hiding coefficient decreases gradually during the iterations, allowing a wider exploration at first and a finer exploitation later.

The selected burrow is then used to update the candidate position:

$$\mathrm{v_i(t+1) = z_i(t) + R\left(r_4 b_{i,r}(t) - z_i(t)\right)} \tag{5}$$

Where $b_{i,r}(t)$a randomly selected is burrow, and r_4 is a uniform random number between 0 and 1. The best solution is maintained for getting stable and energy efficient cluster-head selection. The selected cluster heads allow efficient routing and data transmission based on GTN.

4.3 GTN

GTN is utilized to model the relationships among mobile nodes and learn intelligent routing patterns in the MANET. The nodes are represented by graph vertices and the communication links are represented by graph edges. Features include energy, connectivity, mobility, distance, link-quality information.

The MANET is represented by the adjacency matrix A (0) and the node feature matrix X, and the GTN learns the node relationships via multiple attention channels.

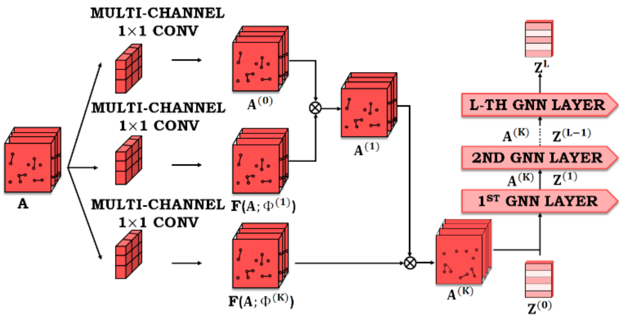

Figure 3: *GTN Architecture*

Where $A^{(k)}$ is the learned graph at the k^{th} GT layer, $\Phi^{(k)}$ are trainable attention parameters and $\widehat{D}^{(k)}$ is the corresponding degree matrix.

$$A^{(k)} = \left(\widehat{D}^{(k)}\right)^{-1}\left[A^{(k-1)} * F\left(A, \Phi^{(k)}\right)\right] \tag{6}$$

The different relationships between nodes are captured by generating multiple graph channels.

The node representation is updated by graph-based aggregation as

$$Z^{(l+1)} = f_{agg}\left(\sum_{c=1}^{c} \sigma\left(\widetilde{D}_c^{-1}\tilde{A}_c^{(k)} Z^{(l)} W^{(l)}\right)\right) \tag{7}$$

Where C is the number of graph channels, $Z^{(l)}$ is the node representation, $W^{(l)}$ is a learnable weight matrix, and f_{agg} is the channel aggregation.

To enhance route intelligence by using self-attention technique which assigns importance of neighbouring nodes.

$$\alpha_{ij} = \frac{exp(q_i^T k_j/\sqrt{d})}{\sum_{mCN_i} exp(q_i^T k_m/\sqrt{d})} \tag{8}$$

Where q_i and k_j are the query and key vectors of node i and j respectively, and d is the feature dimension. Higher attention values mean stronger relations between neighbouring nodes. The final GTN representations are used to predict suitable communication paths based on the learned node relationships and network conditions to realize intelligent and adaptive route selection in MANETs.

5. Results and Discussion

The proposed ARO-GTN based MANET Clustering method is evaluated with existing techniques with important network performance indicators. The analysis is performed on energy consumption, throughput, and PDR, delay and network life time.

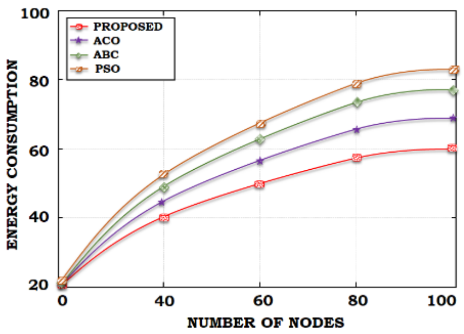

Figure 4: *Energy consumption comparison*

Figure 4 represents the comparison of energy consumption of proposed method with ACO [4], ABC [6] and PSO [14] for different network sizes. The proposed method consistently achieves lower energy consumption 60 J, indicating the better energy efficiency and scalability.

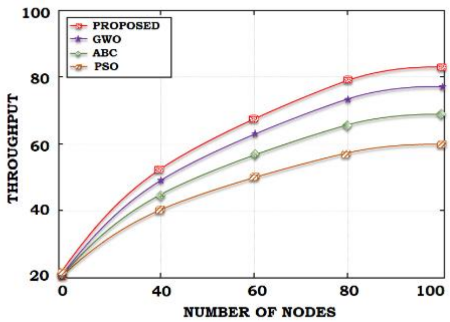

Figure 5: *Throughput comparison of different methods*

Figure 5 presents the comparison of throughput performance of proposed method with GWO [5], ABC [6] and PSO [14] under different network sizes. The proposed method achieves 83 kbps throughput consistently, which reflects better network performance and scalability.

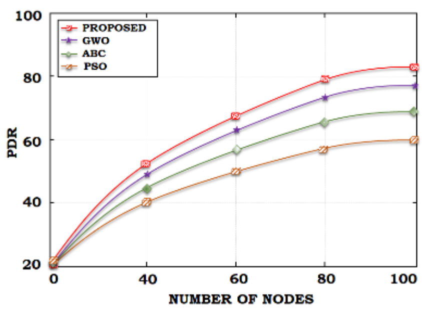

Figure 6: *PDR comparison of different number of nodes*

Figure 6 represents PDR performance of the proposed method with GWO [5], ABC [6] and PSO [14] with different network sizes. The proposed method has achieved 83% PDR which shows the reliable packet transmission and better network performance.

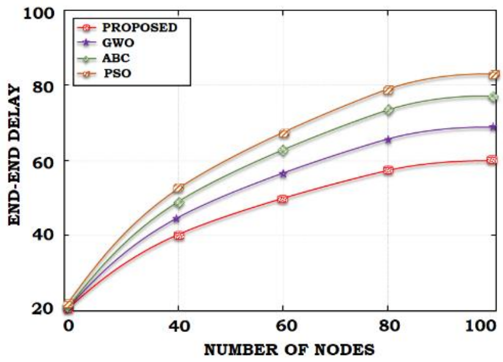

Figure 7: *End-End delay*

Figure 7 shows the comparison of end-to-end delay between proposed method and GWO [5], ABC [6] and PSO [14] under different network size. The proposed method has the least delay OF 60 ms, which means that data transmit faster and the efficiency of the network improved.

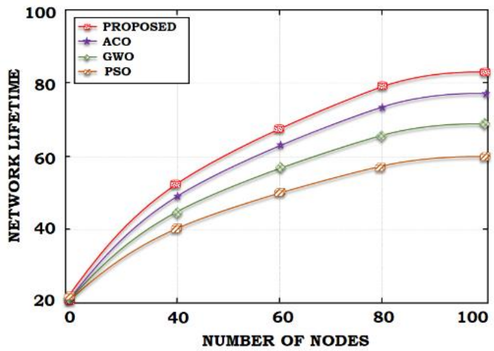

Figure 8: *Network Lifetime*

Figure 8 indicates the comparison of network lifetime of proposed method with ACO [4], GWO [5] and PSO [14] for different network sizes. The proposed method has the highest network lifetime of 83 s, which indicates better energy utilization and longer network operation.

6. Conclusion

In this paper, an intelligent energy-efficient MANET clustering framework based on ARO and GTN is proposed. The ARO algorithm optimizes the selection of energy-efficient cluster heads, while the GTN learns network relations for adaptive and reliable route prediction. The proposed method achieves about 83 kbps throughput, 60 J energy consumption, 83% PDR, 60 ms end-to-end delay and 83 s network lifetime for 100 nodes, which shows better communication and energy efficiency. But further evaluation of the current framework might be needed under highly dynamic mobility conditions and larger network sizes. Future work focus on improving the GTN model to support real-time routing, test more mobility and traffic scenarios, and design adaptive mechanisms for more scalable and reliable MANET communication.

References

1. Minal Patil; Manish Chawhan; Roshan Umate; Abhishek Madankar; Bhumika Neole, Year: 2025, “Energy efficient adaptive clustering with QoS-aware CBRP and grey wolf optimization clustering algorithm for mobile ad-hoc network (MANET)”, Discover Computing, Vol: 28, No: 1, pp. 156.
2. Mohamed Aissa; Maroua Abdelhafidh; Adel Ben Mnaouer, Year: 2021, “EMASS: a novel energy, safety and mobility aware-based clustering algorithm for FANETs”, IEEE Access, Vol: 9, pp. 105506-105520.
3. Narayana MV; Vadla Pradeep Kumar; Ashok Kumar Nanda; Hanumantha Rao Jalla; Subba Reddy Chavva, Year: 2023, “Enhanced energy efficient with a trust aware in MANET for real-time applications”, Computers, Materials & Continua, Vol: 75, No: 1, pp. 587-607.
4. Peng Zhou; Wei Chen; Bingyu Cao, Year: 2025, “An efficient clustering algorithm for enhancing the lifetime and energy efficiency of wireless sensor networks”, Computers, Materials & Continua, Vol: 84, No: 3, pp. 5337-5360.
5. Kudret Yilmaz; Resul Kara; Ferzan Katircioglu, Year: 2025, “Energy-efficient hybrid adaptive clustering for dynamic MANETs”, IEEE Access, Vol: 13, pp. 51319-51331.
6. Vijay U Rathod; Shyamrao V; Gumaste; Ramakrishna Guttula; Shrikant Zade; Ramanpreet Singh, Year: 2025, “Optimization of energy consumption in mobile Ad-Hoc networks with a swarm intelligence-based ABC algorithm”, Discover Applied Sciences, Vol: 7, No: 8, pp. 805.
7. S. Dhanabal; P. William; K. Vengatesan; R. Harshini; VD Ambeth Kumar; S. Yuvaraj S, Year: 2022, “Implementation and comparative analysis of various energy-efficient clustering schemes in AODV”, In International Conference on Big data and Cloud Computing Singapore: Springer Nature Singapore, pp. 297-317.
8. Arvind Kumar; Adesh Kumar; Anurag Vijay Agrawal; Varun Pratap Singh, Year: 2026, “HMC-DSR: An FPGA-Accelerated Clustered Routing Protocol for Scalable and Energy-Efficient MANETs”, Engineering Reports, Vol: 8, No: 4, pp. e70762.
9. Koppisetti Giridhar; C. Anbuananth; N. Krishnaraj N, Year: 2023, “Energy efficient clustering with Heuristic optimization based Ro/uting protocol for VANETs”, Measurement: Sensors, Vol: 27, pp. 100745.
10. Kudret Yilmaz; Resul Kara; Ferzan Katircioglu, Year: 2025, “Energy-efficient hybrid adaptive clustering for dynamic MANETs”, IEEE Access, Vol: 13, pp. 51319-51331.
11. Subhrananda Goswami; Sukumar Mondal; Subhankar Johardar; Chandan Bikash Das, Year: 2025, “Multi-objective function-based optimal path selection for energy efficient routing in MANET using fused locust swarm and dragonfly optimization strategy”, Intelligent Decision Technologies, Vol: 19, No: 9, pp. 68-87.
12. P. Ravi Kiran Varma; Bura Vijay Kumar K. L; Hemalatha; Muhammed Basim Jabar; B. M. Manjula, Year: 2023, “Secure Clustering and

Routing Based on Modified Whale Optimization Algorithm in MANET", In International Conference on 6G Communications Networking and Signal Processing, pp. 37-47

13. G. Rohini; H. C. Kantharaju; B. Gopinathan; Sangeetha, Year: 2023, "ENERGY-EFFICIENT CLUSTER HEAD SELECTION IN MANETS USING FIREFLY ALGORITHM", ICTACT Journal on Communication Technology, Vol: 14, No: 2, pp. 2933.
14. Kudret Yilmaz, Resul Kara; Ferzan Katircioglu, Year: 2025, "Energy-efficient hybrid adaptive clustering for dynamic MANETs", IEEE Access, Vol: 13, pp. 51319-51331.