IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

# AdHoc On-Demand Distance Vector and Artificial Neural Networks (AODV – ANNS) For Neighbor Distance Detection and Efficient Routing Protocol in MANET

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**Abstract-** This research presents an innovative integration of Adhoc On-Demand Distance Vector (AODV) routing protocol with Artificial Neural Networks (ANNs) to improve the effectiveness of neighbor distance identification and routing in MANETs (Mobile Ad hoc Networks). By utilizing ANNs, the system dynamically predicts the proximity of neighboring nodes based on received signal strength, optimizing route discovery. AODV-ANNs demonstrate improved accuracy in neighbor distance estimation and path selection, resulting in more efficient data routing. The hybrid approach enriches the MANET routing protocol landscape by harnessing machine learning for real-time adaptation and intelligent decision-making.

**Keywords**: MANET, AODV, Artificial Neural Networks, routing protocol, neighbor distance detection, efficient routing, machine learning.

## 1. Introduction

Mobile Ad hoc Networks (MANETs) are decentralized wireless networks where mobile devices act as routers, enabling dynamic communication without fixed infrastructure. Routing is challenging due to mobility, limited power, and changing topologies. Protocols determine data paths considering routes, link quality, and energy. Selection depends on network size, mobility, energy, and applications. Researchers enhance protocols to reduce overhead, handle failures, stabilize routes, and optimize energy. MANETs are vital for dynamic environments like disaster recovery, battlefield communication, and rescue ops. Routing protocols are proactive (maintain routes), reactive (find routes on demand), or hybrid, adapting to network needs. Evaluations depend on classification methods. MANETs offer versatile solutions for communication in challenging scenarios.

### 1.1 Shortest Path algorithm

Two fundamental algorithms for determining the shortest path Bellman-Ford algorithm and Dijkstra's algorithm address routing challenges. The process of routing, employing these approaches, follows these steps: Step 1: Each node computes distances to all other network nodes, maintaining the data in a table.Step 2: Nodes share their distance tables with neighboring nodes. Upon receiving these tables, a node calculates the shortest paths to all other nodes and updates its own table accordingly. A routing protocol called Destination Sequenced Distance Vector (DSDV) is tailored for ad hoc networks. This protocol draws inspiration from the distributed Bellman-Ford algorithm.

## 2. Literature Survey

### 2.1 Dijkstra's algorithm

Megbanathanet.al proposed Dijkstra's algorithm is one of the greedy techniques being used in solving shortest path problems. The shortest path algorithm finds efficient routes in graphs from a starting point, applicable in networking, navigation, biology, and more. Dijkstra's Algorithm is common but not always optimal. Megbanathan reviewed Dijkstra's and Bellman-Ford algorithms. Steinhardt noted Dijkstra's traversal techniques ensure shortest routes between graph vertices.

### 2.2 Modified Dijkstra's Algorithm (MDA)

OmoniyiAjokeGbadamosi (2020) et.al proposed Modified Dijkstra's Algorithm. A text file with nodes, edges, and traversal probabilities was used to implement Dijkstra's algorithm. Analysis character by character led to successful route identification in a 40-node graph. The adapted algorithm proved feasible as a substitute in relevant scenarios, showcasing its potential.

### 2.3 Ant Colony Optimization routing protocol

Sinwar D. (2020) et.al proposed a comparative study assessed Ant Colony Optimization (ACOP) Routing against DSDV, AODV, and AOMDV protocols in MANET. Performance metrics included End-to-End Delay, Throughput, and Packet Delivery Fraction. ACOP outperformed other algorithms in delay, throughput, and delivery ratio. DSDV excelled in high node scenarios. Future work may explore more meta-heuristic methods and mobility models to validate Swarm Intelligence's role in optimal routing for MANETs.

### 2.4QOS-GNDA

Pallavi Patil (2020) proposed a new routing protocol called Quality of Service Good Neighborhood Node Detection Algorithms (QOS-GNDA). The Global Network Discovery Algorithm (GNDA) determines efficient routes, yet struggles to quickly handle failures, while dynamic node configurations complicate route stability. Nodes establish temporary paths for packet transfer in Adhoc networks, forwarding for out-of-range nodes. Challenges include topology changes, bandwidth limits, obscured transmitters, and energy constraints. Identifying suitable neighbors becomes vital for reliable communication.

### 2.5Tree Based Multicast Routing Protocol

Kumar Y. A. (2015)et.al proposed a reliable neighbor node selection mesh-based multicast routing protocol for multicast routing in MANETs. This method chooses non-pruned neighboring nodes as subsequent hops for reliable multicast routing, meeting a predefined reliability threshold. It surpasses tree-based protocols in packet delivery and delay via simulations. Multipath techniques distribute load and improve data transmission efficiency.

## 3. Proposed Methodology

### 3.1 Adhoc On-Demand Distance Vector (AODV) Routing Protocol

AODV is a reactive distance-vector protocol with multihop relay. When a node lacks a route to a destination, it triggers a route request (RREQ) propagated by intermediaries. RREQ includes Source/Destination IDs, Broadcast ID, Sequence Numbers, Hop Count, and TTL. AODV prevents Count to Infinity. It has route discovery and maintenance components, utilizing Route Request (RREQ), Route Reply (RREP), and Route Error (RERR) messages. Source sends RREQ with BCastID, Sequence Numbers; neighbors receive RREQ with sequence number and next hop address.

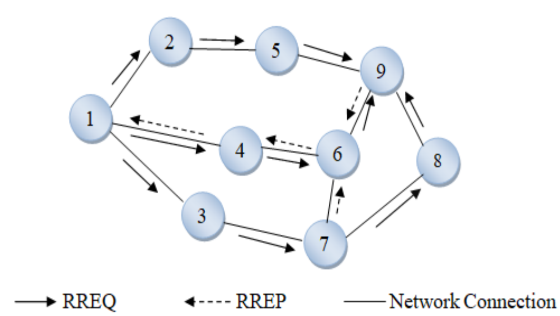


**Figure 1.Adhoc On-Demand Distance Vector**

The timer will be started using TTL each time the source generated an RREQ for the destination. The source will restart the discovery process if the timer runs out again.

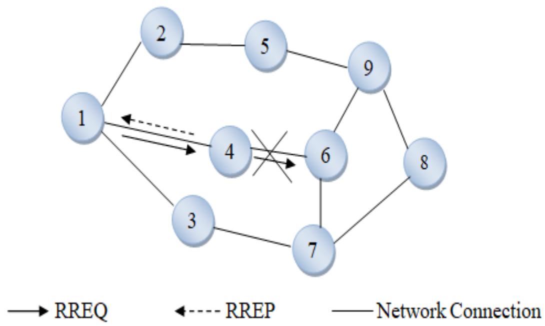


**Figure 2.Route Maintenance process in AODV**

The destination creates and sends the RREP to the source after receiving the RREQ from the source. For instance, even if Nodes 4 and 6 in Figure 2 are destroyed, the 4th node is still sending the RERR message to the source. With a new BCastID and the same Destination sequence number, the source continues the journey. Finally, the walkways have been repaired.

### 3.2 Artificial Neural Networks (ANNs) for Neighbor Distance Detection

Using Artificial Neural Networks (ANNs) for neighbor distance detection in Mobile Ad hoc Networks (MANETs) is an interesting and advanced approach that can provide accurate distance estimates based on observed signal characteristicsANNs are a kind of AI calculation enlivened by the design and capability of the human cerebrum. Research can learn complex relationships between input data (such as received signal strength indicators, signal-to-noise ratios, time delays, etc.) and output values (distances).

Here's how you might apply ANNs for neighbor distance detection in MANETs:

**Data Collection:** Gather a dataset that includes pairs of input features (e.g., RSSI, SNR) and corresponding ground truth distance values. These distance values can be obtained through accurate measurement techniques like UWB ranging or other precise distance estimation methods.

**Data Preprocessing:** Clean and preprocess the dataset. Normalize input features and convert distance values into a suitable format for training. Divide the dataset into training, validation, and testing subsets.

**ANN Architecture:** Design the architecture of the neural network. An input layer, one or more hidden layers, and an output layer are frequently present. It is necessary to know the amount of neurons in each layer, how research is activated, and how research is connected to one another.

**Training:** Train the neural network using the training dataset. During training, the network learns the mapping between input features and distance values. The objective is to reduce the discrepancy between expected and actual distances.

**Validation:** Use the validation dataset to monitor the network's performance during training. This helps prevent overfitting and allows you to fine-tune hyperparameters.

**Testing:** Evaluate the trained network's performance on the testing dataset. Measure the accuracy of distance predictions using metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), or Mean Absolute Error (MAE).

**Deployment:** Once the ANN is trained and tested, you can deploy it to nodes in the MANET. Nodes can input their observed signal characteristics, and the ANN will provide estimated distances based on the learned relationships.

By merging AODV with ANNs for neighbor distance detection, you aim to create a more informed and efficient routing protocol that leverages accurate distance information obtained through machine learning. This approach could potentially lead to better route selection, improved network performance, and enhanced overall MANET operation.

***Algorithm 2: AODV-ANN***
*Step 1: Collect observed signal characteristics (e.g., RSSI, SNR) and accurate ground truth distances.*
*Step 2: Initialize nodes are equipped with trained ANNs and AODV routing.*
*Step3: Integrate AODV-ANN as modify AODV to include ANN-estimated distances.*
*Step 4: AODV's standard route discovery and reply process.*
*Step 5: Calculate the combined metric (CM) for each route using the formula:*

$$CM = (w_{hop} * hop_{count}) + (w_{ANN} * ANN_{estimated_{distance}})$$

*Where:*

$w_{hop}$: *Weight parameter for hop count.*

$w_{ANN}$ : *Weight parameter for ANN-estimated distance.*

$hop_{count}$: *Number of hops in the route.*

$ANN_{estimated_{distance}}$ : *Distance estimated by the ANN.*

*Step 6: Choose routes based on the lowest combined metric value.*

*Step 7: Standard AODV route selection and maintenance process.*

*Step 8: Transmit data packets along chosen routes.*

*Step 9: ANNs periodically updated with new data for adaptive distance estimation.*

*Step 10: It involves retraining the ANN with updated data.*

*Step 11: Assess routing efficiency and accuracy*

## 4. Experiment Results

### 4.1 Packet Delivery Ratio

| No of Nodes | MDA | ACOP | Proposed AODV-ANN |
|---|---|---|---|
| **100** | 60 | 72 | 81 |
| **200** | 63 | 74 | 83 |
| **300** | 65 | 76 | 86 |
| **400** | 73 | 79 | 89 |
| **500** | 75 | 82 | 94 |

**Table 1.Comparison Table ofPacket Delivery Ratio (PDR)**

The varied values of the current (MDA, ACOP) and proposed AODV-ANN were addressed in the comparison table 1 of the packet delivery ratio (PDR). Values for the suggested approach are greater than those for the existing method when compared. The suggested AODV-ANN values start from 81 to 94, while the current values range from 60 to 75 and 72 to 82. The recommended AODV-ANN produces the optimum outcome.

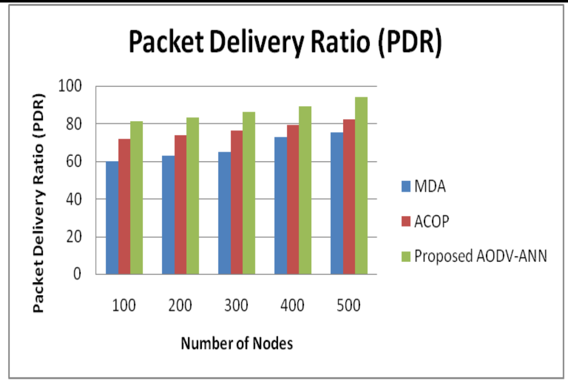


**Figure 3.Comparison chart of Packet Delivery Ratio (PDR)**

The varied values of the proposed AODV-ANN and the existing (MDA, ACOP) packet delivery ratios are shown in figure 3. When comparing the two methods, the suggested technique outperforms the existing method in terms of No. of Nodes in the x axis, Packet Delivery Ratio (PDR) in the y axis, and values overall. The suggested AODV-ANN values start from 81 to 94, while the current values range from 60 to 75 and 72 to 82. The recommended AODV-ANN produces the optimum outcome.

### 4.2 Packet Loss Ratio (PLR)

| No of Nodes | MDA | ACOP | Proposed AODV-ANN |
|---|---|---|---|
| **100** | 56 | 43 | 32 |
| **200** | 65 | 70 | 50 |
| **300** | 75 | 80 | 65 |
| **400** | 88 | 83 | 73 |
| **500** | 93 | 85 | 67 |

**Table 2.Comparison Table ofPacket Loss Ratio (PLR)**

The varied values of the current (MDA, ACOP) and proposed AODV-ANN were addressed in the comparison table 2 of the Packet Loss Ratio (PLR). Values for the suggested approach are greater than those for the existing method when compared. The suggested AODV-ANN values start from 56 to 93 and 43 to 85 and proposed AODV-ANN values start from 32 to 73. The recommended AODV-ANN produces the optimum outcome.

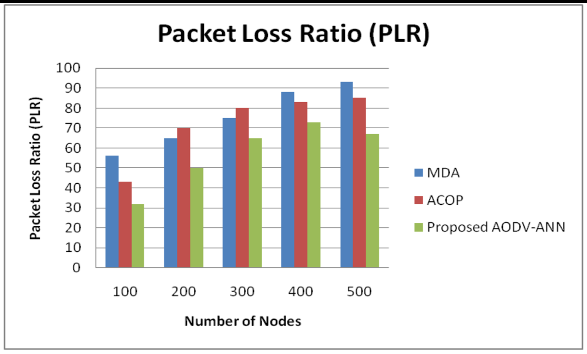


**Figure 4.Comparison Table of Packet Loss Ratio (PLR)**

The varied values of the proposed AODV-ANN and the existing (MDA, ACOP) packet delivery ratios are shown in figure 4. When comparing the two methods, the suggested technique outperforms the existing method in terms of No. of Nodes in the x axis, Packet Loss Ratio (PLR) in the y axis, and values overall. The suggested AODV-ANN values start from 56 to 93 and 43 to 85 and proposed AODV-ANN values start from 32 to 73. The recommended AODV-ANN produces the optimum outcome.

### 4.3 Throughput

| No of Nodes | MDA | ACOP | Proposed AODV-ANN |
|---|---|---|---|
| 100 | 52 | 63 | 70 |
| 200 | 55 | 65 | 75 |
| 300 | 60 | 70 | 80 |
| 400 | 65 | 75 | 85 |
| 500 | 70 | 80 | 90 |

**Table 3.Comparison Table of Throughput**

The varied values of the current (MDA, ACOP) and proposed AODV-ANN were addressed in the comparison table 3 of the Throughput. Values for the suggested approach are greater than those for the existing method when compared. The suggested AODV-ANN values start from 70 to 90, while the current values range from 52 to 70, 63 to 80. The recommended AODV-ANN produces the optimum outcome.

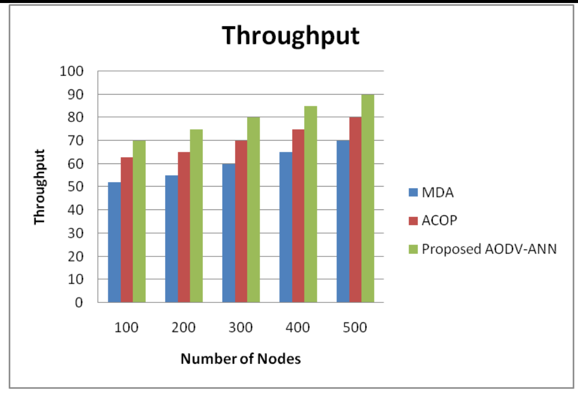


**Figure 5.Comparison Chart of Throughput**

The varied values of the proposed AODV-ANN and the existing (MDA, ACOP) Throughput are shown in figure 5. When comparing the two methods, the suggested technique outperforms the existing method in terms of No. of Nodes in the x axis, Throughput in the y axis, and values overall. The suggested AODV-ANN values start from 70 to 90, while the current values range from 52 to 70, 63 to 80. The recommended AODV-ANN produces the optimum outcome.

### 4.4 Energy Consumption

| No of Nodes | MDA | ACOP | Proposed AODV-ANN |
|---|---|---|---|
| **100** | 100 | 95 | 85 |
| **200** | 90 | 85 | 80 |
| **300** | 80 | 75 | 60 |
| **400** | 70 | 62 | 40 |
| **500** | 60 | 45 | 20 |

**Table 4.Comparison Table of Energy Consumption**

The varied values of the current (MDA, ACOP) and proposed AODV-ANN were addressed in the comparison table 4 of the Energy Consumption. Values for the suggested approach are greater than those for the existing method when compared. The suggested AODV-ANN values start from 85 to 20, while the current values range from 100 to 60, 95 to 45. The recommended AODV-ANN produces the optimum outcome.

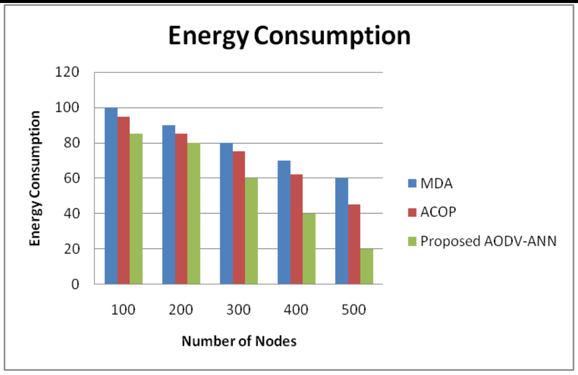


**Figure 6.Comparison Chart of Energy Consumption**

The varied values of the proposed AODV-ANN and the existing (MDA, ACOP) Energy Consumption are shown in figure 6. When comparing the two methods, the suggested technique outperforms the existing method in terms of No. of Nodes in the x axis, Energy Consumption in the y axis, and values overall. The suggested AODV-ANN values start from 85 to 20, while the current values range from 100 to 60, 95 to 45. The recommended AODV-ANN produces the optimum outcome.

## 5. Conclusion

The synergy of AODV and Artificial Neural Networks in the AODV-ANNs hybrid presents a promising advancement in MANET routing. The integration of neural networks for neighbor distance estimation enhances the accuracy of route selection, leading to more efficient data transmission. The approach not only adapts to the dynamic nature of MANETs but also provides a stepping stone toward more intelligent and self-optimizing network protocols. The success of AODV-ANNs encourages further exploration of machine learning techniques to refine and hence network operations in mobile ad hoc environments.

## References


1. Gbadamosi, O. A., &Aremu, D. R. (2020). Design of a Modified Dijkstra's Algorithm for finding alternate routes for shortest-path problems with huge costs. 2020 International Conference in Mathematics, ICMCECS doi:10.1109/icmcecs47690.2020.240873 10.1109/ICMCECS47690.2020.240873.
2. Meghanathan, D. N. (n.d.). (2012) Review of Graph Theory Algorithms. MS: Department of Computer Science, Jackson State University, unpublished.
3. Kevin M. Curtin, Network Analysis in Geographic Information Science: Review, Assessment, and Projections Vol. 34, No. 2, 2007, pp. 103-11 (CAGIS) Cartographic and Geographic Information Society, published.
4. Sinwar, D., Sharma, N., Maakar, S. K., & Kumar, S. (2020). Analysis and comparison of ant colony optimization algorithm with DSDV, AODV, and AOMDV based on shortest path in MANET. Journal of Information and Optimization Sciences, 41(2), 621–632. doi:10.1080/02522667.2020.1733193.
5. Kumar, Y. A., & Sachin, T. (2015). A Tree Based Multicast Routing Protocol Using Reliable Neighbor Node for Wireless Mobile Ad-Hoc Networks. Proceedings of the 4th International Conference on Frontiers in Intelligent Computing: Theory and Applications (FICTA) 2015, 455–465. doi:10.1007/978-81-322-2695-6_38 .
6. Bhatia, R., & Gupta, R. (2015). Comparative analysis of AODV, DSDV, OLSR and DSR: Routing protocols in MANET. International Journal of Computer Applications, 119(15), 1-6.
7. Zhang, L., & Qian, Y. (2013). A novel artificial neural network for mobile ad hoc networks topology discovery. Wireless Personal Communications, 73(2), 417-434.
8. Mishra, R., & Tripathi, P. (2012). Enhancing AODV protocol with genetic algorithm for efficient routing in MANET. Procedia Engineering, 38, 1174-1183.
9. Gao, L., & Xiong, H. (2017). An Improved AODV Routing Protocol for Mobile Ad Hoc Networks. Wireless Personal Communications, 94(1), 109-123.
10. Grover, P., & Malhotra, J. (2019). Survey on Neighbor Discovery Techniques in MANETs. Wireless Personal Communications, 104(4), 1749-1776.