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MALICIOUS ATTACK PREVENTION IN MOBILE AD-HOC NETWORK USING NODE CLUSTERING TECHNOLOGY

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ABSTRACT
The performance of a mobile ad hoc network (MANET) relies on factors such as traffic volume and node speed, leaving room for potential enhancements, particularly when considering routing and node energy consumption. Traditional routing techniques have been employed to boost performance metrics like throughput and latency. Researches shown that optimum network topology is positively enhancing the overall nodes resistance to the malicious attacks. Malicious nodes will mimic the behaviors of destination node and try to receive the payload from the sender and drop it out. Node clustering will block the routing paths as each node in a cluster will forward its packets to unified destination which make it difficult to the cluster node to mimic. This study establishes a connection between the base station node and hosting nodes, utilizing 150, 250, and 350 nodes, along with four cluster heads, to implement AODV-based routing through a clustering strategy. Communication between nodes is established using deep learning technique for node clustering. By employing an improved clustering method, the throughput has been enhanced significantly, increasing from 83.92% (baseline method prior to node clustering) to 92.73%.

Keywords:- Host, AODV, ADHOC, FFNN, Optimization, Clustering, PSO.

INTRODUCTION
Node clustering in wireless sensor networks is a technique aimed at improving the performance of the network by organizing sensor nodes into clusters. This approach offers several benefits, including enhanced energy efficiency, improved network scalability, reduced communication overhead, and increased network lifetime [1]. By clustering sensor nodes, the network can be divided into smaller groups or clusters, with each cluster having a designated cluster head or coordinator. The cluster heads play a crucial role in managing and coordinating the activities within their respective clusters [2]. They collect data from the member nodes, aggregate and process it locally, and then transmit the relevant information to the base station or the sink node. Node clustering provides several performance improvements in wireless sensor networks [3]. Cluster-based communication enables the use of advanced energy-saving mechanisms. Sensor nodes can employ techniques like sleep scheduling or duty cycling, where nodes periodically alternate between active and sleep states, conserving energy and prolonging the network lifetime [4]. Clustering allows for easier network expansion. As new nodes are added to the network, they can be assigned to existing clusters or form new clusters, thereby ensuring efficient scalability without sacrificing network performance. By reducing the number of messages transmitted in the network, clustering reduces the overall communication overhead. The cluster heads handle intra-cluster communication, aggregating and compressing data before forwarding it to the base station [5]. This results in reduced energy consumption and improved network efficiency. Network resilience can be improved using this technique by isolating faulty or failed nodes within a cluster. In the event of a node failure, the cluster head can initiate reorganization and redistribute the responsibilities among the remaining nodes, ensuring continued network operation [6] [7]. Overall, node clustering is an effective technique for improving the performance and efficiency of wireless sensor networks. It optimizes resource utilization, reduces energy consumption, and enhances network scalability and fault tolerance, leading to more robust and reliable network operations [8].

The process of forming clusters involves selecting cluster heads and assigning member nodes to each cluster [9]. Various algorithms and protocols are used to determine the cluster head selection criteria, such as residual energy, node proximity to the base station, or node density [10]. Once the cluster heads are elected, member nodes join their respective clusters based on specific rules, which can be predetermined or dynamically determined [11]. Cluster heads play a vital role in data aggregation [12]. They collect data from member nodes within their cluster, aggregate it, and perform necessary processing before transmitting the summarized information to the base station or sink node [13]. Data aggregation reduces the amount of data traffic in the network, minimizing energy consumption and communication overhead. The cluster heads are responsible for managing the cluster and ensuring its proper functioning [14]. They handle tasks such as cluster formation, maintaining cluster membership, and dealing with node failures or additions. In some cases, cluster heads can also perform data fusion or decision-making tasks to reduce the amount of data transmitted to the base station. In addition to basic clustering, hierarchical clustering techniques can be employed to form multi-level clusters [15]. This approach creates a multi-tiered network structure with multiple levels of cluster heads. Hierarchical clustering provides more efficient data aggregation and better scalability in large-scale sensor networks [16]. Dynamic clustering allows for adaptive reconfiguration of clusters based on changing network conditions. It enables cluster reformation, cluster head rotation, and dynamic adjustment of cluster sizes to accommodate network dynamics, node failures, or energy variations [17]. Dynamic clustering algorithms aim to optimize energy efficiency, network stability, and performance in dynamic environments. Node clustering has widespread applications in various domains. It is commonly used in environmental monitoring, surveillance systems, healthcare, agriculture, and industrial monitoring. By optimizing resource utilization and improving network efficiency, clustering enables better data collection, analysis, and decision-making in these application areas.

Node clustering in wireless sensor networks is a powerful technique that provides numerous benefits, including energy efficiency, scalability, reduced communication overhead, fault tolerance, and adaptability to dynamic environments [18]. These advantages contribute to more efficient and robust network operations, making node clustering a fundamental strategy for enhancing the performance of wireless sensor networks. In this paper, dynamic node clustering is proposed using deep learning paradigm in order to enhance the performance of network, the outcomes are compared with two models which were previously designed: no cluster and standard cluster.

In this paper, we intended to enhance the network performance by adopting a smart clustering model, which sets the nodes locations where less packets drop can take place. The enhancement of the time and network performance through reduction the loses in the packets is achieved using the PSO based neural network as algorithm to perform a supper clustering. The remaining parts of the paper as node clustering techniques overview is in section 2, supper clustering is detailed in section 3.

NODE CLUSTERING

A clustering strategy model employing 150, 250, and 350 nodes is currently being mobilized, with each node operating independently. This model allows for the utilization of routing protocols such as AODV designed to be self-starting in an environment of mobile nodes, withstanding a variety of network behaviors such as node mobility, link failures and packet losses. The construction of the model refers to Table 1 as a guide. Initially, data transmission was conducted without the assistance of clustering technology when the first scenario was established. However, when the second scenario was introduced, data transmission with the aid of clustering technology was tested and proven successful. Figure 1 depicts the network topology, consisting of host nodes intended to communicate with each other to transmit data to the main node (base station), represented by the dark orange color.

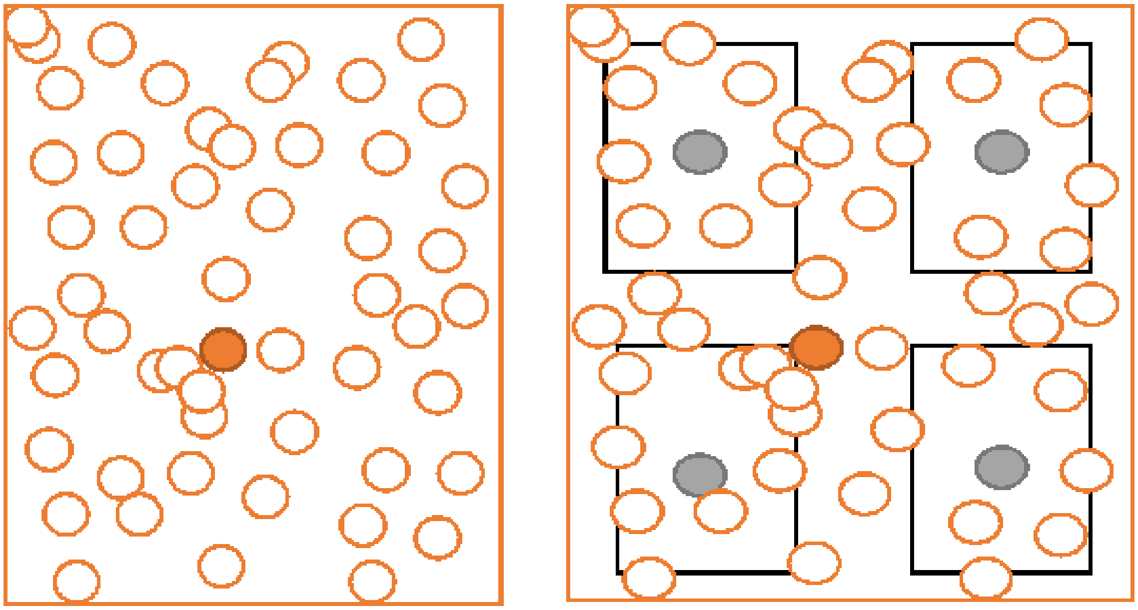

Figure 1 (a) Figure 1 (b)

Figure 1: network topology outline demonstrating the host nodes and cluster heads; (a) no cluster case, (b) near-far distance based clustering.

In Figure 1 (b), clustering is implemented to group the nodes into four clusters, where each cluster transmits data to its respective cluster head (represented by the brown color). Based on Table 1, the model was implemented with nodes operating at a random speed of 10 m/30 sec. Initially, all nodes had direct access to the base station without utilizing any clustering methods (as shown in Figure 1 (a)). Subsequently, the nodes were connected to the four cluster heads located at the base station, with one cluster head positioned at the center of each cluster (as depicted in Figure 1 (b)). The host nodes navigate the arena while remaining linked to the nearest cluster head. Four clusters were formed based on the rectangular topography of the system, with each corner housing a cluster to cover the entire arena.

Supper Clustering

The Feed Forward Neural network-based PSO technique clusters nodes and assigns mobile nodes to the head nodes in each cluster to enhance network performance Neural network is used to produce the location of the nodes and cluster head

Neural networks can be used for node clustering in wireless sensor networks (WSNs) in several ways. Here's a step-by-step explanation of how neural networks can be applied for node clustering in WSNs:

(a) **Data Representation:** The first step is to represent the sensor data in a suitable format for input to the neural network. Each sensor node in the WSN collects data, such as temperature, humidity, or motion readings. This data needs to be transformed into a feature vector or matrix representation that can be fed into the neural network.

(b) **Feature Extraction:** Neural networks can extract relevant features from the sensor data to aid in cluster formation. The network learns to identify patterns, correlations, or similarities among the data collected by different nodes. By extracting meaningful features, the neural network can capture important information for cluster formation.

(c) **Training:** The neural network is trained using a labeled dataset that includes input data (e.g., sensor readings) and corresponding cluster labels. The labels indicate the cluster to which each node belongs. The network is trained to predict the cluster labels based on the input data.

(d) **Cluster Head Selection:** Once the neural network is trained, it can be used to select cluster heads. The trained network takes input from the sensor nodes' data and outputs the probability or membership scores of each node belonging to a specific cluster. Based on these scores, the nodes with the highest scores can be chosen as cluster heads.

(e) **Adaptive Clustering:** Neural networks can enable adaptive clustering approaches by continuously updating the network's parameters based on changing network conditions. The network can be fine-tuned using online learning techniques, allowing it to adapt to dynamic network characteristics such as node failures, changes in data patterns, or network topology alterations.

PSO-FFNN

PSO algorithm and FFNN algorithm are both existing, also the hybridization between them was made in previous works but not in the context of node clustering, it had been used for other applications in data mining and machine learning

In the field of network communication, node clustering is essential for maximizing network performance and reducing packet losses, particularly in large-scale networks. Feed Forward Neural Networks (FFNN) have shown promise in node clustering; however, achieving the desired results requires effective FFNN parameter optimization. In order to improve network performance by reducing packet losses, this contribution investigates the use of the Particle Swarm Optimization (PSO) algorithm to optimize the FFNN algorithm for node clustering.

The process of grouping network nodes with comparable features or functionalities together is called node clustering. Nodes in a network can be any number of things, including switches, routers, and even end-user devices. These nodes can be clustered to increase fault tolerance, load balancing, and network efficiency. Network administrators can lower latency and packet losses by strategically clustering nodes to shorten the distance that packets must travel.

Because Feed Forward Neural Networks (FFNN) can learn intricate relationships from the network data, they are being used more and more in node clustering. Effective node clustering requires the ability to recognize patterns and correlations in network traffic, which FFNNs provide. However, the choice of hyper parameters, including the number of hidden layers, neurons per layer, and learning rates, has a significant impact on how well FFNN models perform. Manually adjusting these parameters can be difficult, and using less-than-ideal values can lead to ineffective clustering and more packet losses.

Particle Swarm Optimization is an optimization method inspired by nature, which mimics the actions of a swarm of particles or a flock of birds looking for the best solution in a multi-dimensional space. PSO can be used in the context of FFNN optimization for node clustering to automatically adjust the hyper parameters. PSO adjusts the FFNN's parameters iteratively, assesses their effectiveness with relevant metrics (such as packet loss rate), and directs the search towards the ideal collection of hyper parameters.

Hyper parameter Adjustment: PSO assists in determining the best FFNN hyperparameter configuration, which is essential for precise node clustering. To find the combination that reduces packet losses, it methodically searches the parameter space.

PSO uses performance-based hyper parameter updates to intelligently update the parameters, which speeds up the convergence of FFNN training. As a result, the FFNN model can be trained faster and node clustering in dynamic networks can occur in real-time or almost in real-time. PSO continuously optimizes the FFNN to adjust to shifting network conditions. This flexibility is essential to maintaining the effectiveness of the clustering in situations where network dynamics change over time. Network performance is improved, leading to faster and more dependable communication, by reducing packet losses and optimizing node clustering. Network managers can more easily implement and maintain effective node clustering when automation via PSO eliminates the need for manual FFNN hyper parameter tuning. The PSO-optimized FFNN technique is appropriate for a range of network sizes and types because it can scale to manage larger and more complex networks. Reducing packet losses through the use of the PSO algorithm to optimize the FFNN algorithm for node clustering presents a viable path toward improving network performance. By utilizing machine learning and optimization, this method configures FFNN hyper parameters intelligently, leading to enhanced network communication and more effective node clustering. These creative solutions are becoming more and more necessary as network technology develops to preserve the dependability and effectiveness of contemporary networks.

Neural network is used to produce the location of the nodes and cluster head by performing the following steps:

1) For different types of topologies, the node location and as well as the cluster head location and overall throughput in this particular topology of the network is made.
2) The data is being made for 100 iterations of the network topologies.
3) The data is being used to train the neural network to produce the optimum (cluster head location) for known locations of nodes. The overhead selection should be ensuring the maximum packets throughput.

The Particle Swarm Optimization (PSO) algorithm is used in this work to enhance the performance of a feed-forward neural network (FFNN) [19]. By applying the PSO algorithm to an FFNN, the weights and biases of the network is optimized to enhance its performance. The algorithm's exploration and exploitation capabilities enable it to search for better solutions in the weight space, thereby improving the FFNN's ability to learn and make accurate predictions. The PSO algorithm helps to overcome the problem of getting stuck in local optima by maintaining both individual and global best positions, ensuring a balance between exploration and exploitation [20][21]. So-to-say, integrating the PSO algorithm with an FFNN offers a powerful approach for optimizing the network's parameters and improving its performance in various tasks, including classification, regression, and pattern recognition

Evaluation and Optimization

The performance of the clustering results is evaluated by comparing the predicted cluster labels with the ground truth labels. Metrics such as accuracy, energy efficiency, or network lifetime is used to assess the effectiveness of the clustering approach. The neural network's architecture and parameters is optimized to improve clustering performance.

The following measures are used to assess networking performance:

PDR: The packet delivery rate (PDR%) is the proportion of packets that were successfully transmitted throughout the network, as assessed for each network node. Eq.1 [14] contains details on packet delivery rate.

$$PDR = \frac{N}{T} \times 100\% \qquad (1)$$

Where

- T is the total number of packets travelling through the network from source nodes to destination nodes.
- N represents all of the packets that were received at the destination station.

Packets that are dropped during transmission from the source node to the destination nodes make up the total number of dropped packets (DP) (Eq.2) [15] .

$$DP = M - N \qquad (2)$$

Where

M represents all of the created packets.

Latency: The time it usually takes for a packet to go from its source to its destination, measured in seconds after the destination node receives the packet and verifies that it got there.

The number of packets that a source node sends to a destination node is known as throughput (Eq.3) [16].

$$Th = \frac{N}{M} \times 100\% \quad (3)$$

PDoR: The packet drop rate is quantity of packets discarded over the connection duration (transmission interval) (Eq.4) [17].

$$PDoR = \frac{DP}{T} \quad (4)$$

Table 1: Delivery rate vs nodes number in all cases

Number of Nodes	Delivery Rate% @ No Clustering	Delivery Rate% @ standard Clustering	Delivery Rate% @ Supper Clustering
150	47.0666667	58.1333333	66.3333333
250	234.933333	258.866667	259.6
550	529.8	533.666667	541.733333

Table 1 presents a thorough analysis of the delivery rate performance using different approaches in relation to the number of nodes. Notable improvements are highlighted, especially in the super clustering case, thanks to the PSO-FFNN approach. An increase in the delivery rate indicates improved network efficiency. It is a crucial metric that assesses the successful transfer of data packets within a network.

Table 1 clearly illustrates the trend of the delivery rate rising as the number of nodes increases. This finding is consistent with the expected behavior of highly optimized network clustering techniques, which may enable a greater number of nodes to gain from efficient clustering schemes. But the PSO-FFNN approach is unique because it can greatly increase the delivery rate, especially in the super clustering scenario. This impressive increase can be ascribed to the decrease in packet losses enabled by the node clustering based on PSO-FFNN. The proposed model's unique feature of precisely assigning cluster heads within the network is the primary factor responsible for this improvement. The PSO-FFNN algorithm is very good at finding the best nodes to be cluster heads in super clustering. These cluster heads connect to the greatest number of nodes by placing themselves in a strategic manner throughout the network. Reducing packet losses is made possible in large part by this exact cluster head assignment. Cluster heads serve as the main hubs for communication within their respective clusters when they are positioned strategically. This lowers latency and improves network efficiency by limiting the distance data packets must travel to reach their destination.

The fact that the super clustering case utilizing the PSO-FFNN method showed an increase in delivery rate is evidence of the model's ability to optimize cluster head assignment, meaning that cluster heads are positioned in the best possible way to act as effective data relay points. This strategy therefore results in a significant decrease in packet losses and, as a result, a noticeable increase in the network's delivery rate. Similarly, for the same reason the metrics given on Table 2 , 3 and 4 are enhanced.

Table 2: Drop rate vs nodes number in all cases

Number of Nodes	Drop Rate% @ No Clustering	Drop Rate% @ standard Clustering	Drop Rate% @ Supper Clustering
150	27.6	16.5333333	8.33333333
250	45	21.0666667	20.3333333
550	121.133333	117.266667	109.2

Table 3: Delay rate vs nodes number in all cases

Number of Nodes	Delay % @ No Clustering	Delay % @ standard Clustering	Delay% @ Supper Clustering
150	13.55	12.22	9.66
250	18.58	17.84	15.34
550	33.6	43.37	33.3

Table 4: Throughput vs nodes number in all cases

Number of Nodes	Throughput% @ No Clustering	Throughput% @ standard Clustering	Throughput% @ Supper Clustering
150	63.0357143	77.8571429	88.8392857
250	83.924744	92.4743987	92.7363658
550	81.3908234	81.9848423	83.2240885

OBSERVATIONS:

1) **At No-Clustering:** In this scenario, it is absorbed that time delay is increasing when the number of nodes increases, same for the number of drop packets and packet drop rate. However, throughput is slightly higher in case of 250 packets and that is due to the random mobility of the nodes.

2) **At Standard Clustering:** In this scenario, it is absorbed that all results is being enhanced after introduction of the clustering method over the standard method of the previous scenario.

3) **At Supper Clustering:** throughput of the network is increased from the level of standard clustering and no-clustering to be optimum. Similarly, delay is reduced, dropping rate is reduced and delivery rate increased.

CONCLUSION

Wireless communication over short distances relies on mobile ad hoc networks (MANETs) that connect hosts. The quality of communication is influenced by the volume of data being transmitted and the number of network nodes involved. The motivation of this work was to optimize the network performance through cluster head selection optimization which will resist the malicious activity in the network.

In this study, we investigate the effectiveness of cluster routing with and without the use of two seniors. We evaluate the performance of the routing protocol without clustering at 150, 250, and 350 nodes. The base station node, located at the center of the network coverage area, receives data from the host nodes. Nodes within the base station's communication range can directly communicate with it, while nodes beyond the coverage area establish multi-hop connections through other valid nodes. On the other hand, when four clusters are formed for the same number of nodes, cluster-based routing is employed. The near-far theorem is utilized to establish links between host nodes and cluster head nodes, with a speed limit of 10 km/h for each node. The PSO-FFNN algorithm enables mobile nodes to quickly and effectively select cluster heads. The results demonstrate that supper cluster-based routing (using PSO-FFNN) significantly improves network performance compared to non-clustered routing. The clustering strategy's effectiveness is greatly enhanced by the improved clustering technique employed in this study (as indicated in the provided pseudo code). The utilization of the clustering strategy leads to an optimum throughput value as well as reduction in dropping rate and improvement of delay and delivery rate.

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