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Research Article

A Classifier-Driven Deep Learning Clustering Approach to Enhance Data Collection in MANETs

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ABSTRACT

The conventional clustering and routing approaches used in mobile ad hoc networks (MANETs) may fail to work effectively in a dynamic network environment where nodes are highly mobile and the traffic load may also vary significantly. These limitations result in negative effects such as high packet drop rates, delays in data transmission, and low delivery rates, which make these methods unfit for modern high-density networks. To overcome these issues, this paper proposes a new deep learning-based classifier for adaptive clustering in MANETs. Through the use of machine learning algorithms, the proposed method is able to adapt to node clustering through node behavior, mobility, and content distribution in real-time, thus improving network performance. This work compares the performance of the network on networks that contain 50, 100, and 200 nodes via a clustering algorithm. The performance parameters considered include the delivery ratio, packet drop ratio, and end-to-end delay. The evaluation findings show that the developed deep learning-based classifier is far more effective than the non-clustered and conventional clustering approaches are. In particular, the classifier approach provides a delivery rate of up to 89.4%, which is significantly better than that of the baseline scenarios and decreases packet drop rates by more than 70%, especially in high-density node scenarios. In addition, the proposed approach reduces the network delay and effectively handles the inherent dynamic characteristics of MANETs.

1. INTRODUCTION

Node clustering is one of these techniques where we can enhance the performance of a network, and in it, sensor nodes are grouped into clusters. Several such advantages have already been realized with this approach, which is energy efficient, as it reduces the need for communication sharing among different applications executing in networks along with their scalability and longer lifetime [1]. The coordination and organization of activities in a network can be organized in a more systematized manner by dividing a large area into smaller clusters with their own cluster heads [2]. This cluster-based communication also enables energy saving mechanisms such as sleep scheduling, energy conservation and network lifetime [2], [3]. Clustering, in turn, ensures expansion of the network and makes the networks scalable with lossless performance [4]. However, reducing the communication overhead as well as intracluster communications can save energy and make the network more efficient [4]. Second, it enhances the resilience of the network by grouping nonsuitable or disconnected nodes and still keeping them operational [3], [5].
Node clustering helps improve the performance of wireless sensor networks, maximizes resource utilization and increases fault tolerance capabilities, increasing network stability and reliability [6]. Formation is performed in a clustered fashion where it selects cluster heads and assigns member nodes on the basis of a predetermined (deterministic/nondeterministic) process [7]. Cluster heads serve as a vital part of data aggregation; before forwarding to the base station, the cluster heads aggregate the collected data and process it [5]. Data aggregation is an operation that reduces energy consumption and communication overhead by reducing the network load. The cluster heads are also responsible for managing the formation of each of their respective clusters, maintaining membership as needed, and handling node failures/additions [8].
Hierarchical clustering techniques can generate multilevel clusters to aggregate data in a more efficient and scalable manner within large-scale sensor networks [9]. Dynamic clustering algorithms change clusters on the basis of current network conditions, which optimize energy efficiency, stability, and performance [10]. Node clustering has been implemented in some areas, such as industrial monitoring, agriculture for high crop production and water installation services, healthcare

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to obtain records of patients [11], surveillance systems, and environmental and monitoring. Therefore, clustering of the nodes in wireless networks increases performance, efficiency, and reliability.
Various clustering schemes have been proposed for efficient data acquisition in WSNs and MANETs or mobile ad hoc networks. A survey on clustering algorithms that emphasized energy efficiency was described in [1]; however, many of these techniques do not perform well in a dynamic environment where nodes are mobile. Another approach was presented in [2], where LEACH, a clustering protocol that distributes energy overheads among nodes, was described; however, owing to its static clustering, the packet drop rates increase with increasing number of nodes in the network. Similarly, distributed clustering approaches do not meet the needs of real-time dynamic adaptability for today's networks [10]. However, more recent attempts include the use of machine learning models in the PSO algorithm with neural networks [11], but these methods experience slow convergence problems in real-time, high-dimensional environments.
The limitations of the above approaches are avoided in our proposed deep learning-based classifier, which adapts clustering approaches on the basis of node mobility and network conditions. This approach is highly adaptive, allowing for real-time optimization of network performance rates, such as packet drop rates of up to 70% and other aspects of delivery efficiency in high-density environments. In contrast to previous clustering algorithms, our algorithm can adapt to the changing structure of the network and thus save energy and minimize latency.
The authors suggested the use of a deep learning paradigm within the framework of dynamic node clustering to improve network performance. We compare the results with those of the two previously introduced models: those without clusters and those with standard clusters. This approach makes use of deep learning strategies to improve energy efficiency and scalability, tolerate faults, and adapt to dynamic environments. The outcomes obtained from our proposed approach of dynamic node clustering will assist in evaluating the benefits and efficiency of deep learning in wireless sensor networks.
The performance of wireless sensor networks depends on the number of nodes as well as the clustering approach used[12]. Traditional optimization approaches have been presented to achieve efficient network performance [13], [14]. The nature of a network environment is highly dynamic, and the traditional optimization technique does not accurately express the dynamic features of networks. Therefore, this article aims to report how nodal density and multihopping affect various network performance metrics, such as time delay, packet drop rate, and throughput.

The following sections are divided into the methodology used to address the research problems, the results and discussion, and the conclusions.

1.1 Mobile Ad hoc Network

Mobile ad hoc network (MANET): MANET supports ad hoc wireless networks that contain several mobile hosts. These systems are considered multihop wireless relays in which normal operating host features act as routers, serving to sustain involvement and maintain connections between various other close-to-host clients. All routable networking environments are realized on top of some ad hoc link layer networks. A MANET defines a collection of wireless mobile nodes that self-configure to form an arbitrary topology without any support or routing from preexisting infrastructure. The network topology in the MANET is dynamically changing (Figure 1). The nodes are moving randomly and are not fixed at a place. Each node has a routing function, and it sends the traffic to other specified nodes in the network. When the mobile device changes from one location to another, its resources and communication range differ.

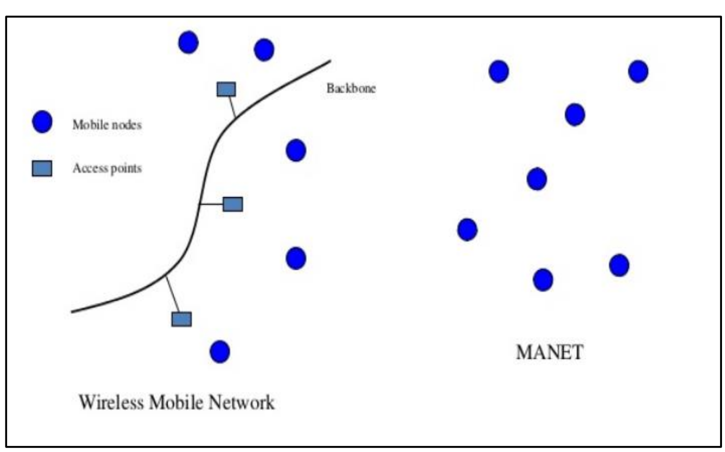

Fig. 1. A MANET Network

2. METHODOLOGY

Different methodologies for node clustering in wireless sensor networks (WSNs) have provided facilities that use neural networks. The application of node clustering in WSNs via a neural network is illustrated as follows:

- **Data** processing: In the first stage, data are converted from all sensors at a timestep in a format that can be given to our neural network. Data from the sensor nodes in the wireless sensor network (WSN) include information about temperature, humidity and other measures of human mobility. With the raw data in hand, it needs to be transformed into a feature vector or matrix (after which it must also be normalized) that can be fed as input to the neural network [8].
- **Feature Extraction:** Neural networks are capable of extracting the relevant features from sensor information so that these features can be used to form clusters. Neural networks learn to detect patterns, correlations, and similarities by analysing the data from different nodes. This extraction process allows the network to learn important information for clustering [15].
- **Training:** In this step, the neural network is trained by choosing a labelled dataset consisting of input data (sensor readings) and related cluster labels. These are labels that indicate the module affiliation of each node. At the end of training, the network has learned to predict cluster labels from input data, which means that it understands how patterns and relationships are embedded in a collection of samples.
- **Cluster Head Identification:** After training, the neural network is ready to identify cluster heads. Once the sensor node data are input to the trained network, the output will be in terms of probabilities or scores, i.e., a value that represents how likely each note is to appear in a different cluster. Nodes that obtain the highest scores are then chosen as cluster heads to carry out and coordinate activities between nodes that belong to the same clusters.
- **Adaptive Clustering:** Neural networks support adaptive clustering techniques that adjust the network parameters on the basis of changing network behavior. Whenever the network needs to update its method of operation, due to changing conditions in the form of shifts in network topology, changes in patterns of data, or failure of nodes, online learning provides it with an opportunity to recalibrate. This adaptive capability ensures the effectiveness and efficiency of the clustering approach in a dynamic WSN.

In this manner, neural network-based node clustering in WSNs can help achieve better cluster formation and improve overall performance by considering the dynamic nature of networks. Neural networks are flexible and learning-based, on which more efficient data processing, optimized resource utilization, and improved overall performance in WSNs can be achieved.

2.1 Proposed Clustering Model

A clustering strategy model is followed, and for that 50, 100 and the individually acting two hundred nodes are used independently in this study. It contains the experimental design, data collection and how it was analysed. The evaluation was based on throughputs, time delays and packet drop ratios.

The network configuration, clustering strategy and data collection data were among the components of the experimental setup. As far as the network configurations are concerned, this work makes use of mobile ad hoc networks (MANETs) using 50, 100 and 200 nodes with four numbers of CHs.

For this purpose, node counts of 50, 100 and 200 were chosen for different densities of the network and to assess the scalability of the proposed clustering in distinct MANET settings. The reduced number of nodes (50) is intended to mimic specific instances of network implementation, for example, sensor-based observations, where fewer nodes are required to interconnect over a limited area. The 100-node scenario depicts a fairly dense network, as seen in the urban communication or disaster recovery networks, where mobility and data exchange are relatively active. Finally, the 200-node setup evaluates the system's performance in high-density networks, such as battlefield communications or massive IoT networks, where scalability and network congestion are vital parameters. By selecting these three different node densities, it becomes possible to evaluate how the clustering approach performs at different levels of complexity of the network while minimizing the overhead in packet delivery, throughput and energy consumption.

The use of four cluster heads is justified here on the basis of the ability to collect data while simultaneously saving energy in a distributed MANET environment. The network has four cluster heads, which makes it possible to spread the nodes well across the clusters and at the same time reduce the overhead of the communication. This setup improves scalability because the cluster head is responsible for some nodes instead of being a single point of control that may cause bottlenecks when dealing with a large number of nodes, for example, 200 nodes. Moreover, the deployment of cluster heads helps alleviate the load of each node and thus enhances the energy efficiency by minimizing the transfer of unimportant data. This makes it possible for the network to perform efficiently on a small scale as well as on a large scale without much impact on performance or power consumption.

A clustering strategy was designed that uses the AODV routing algorithm and deep learning for crane movement. To achieve this, three routing algorithms—Q-Learning, SARSA and DQN—were implemented to learn and enhance routing decisions in MANETs. In addition, the data from the network nodes were also collected, and performance metrics such as throughput, time delay, and packet drop rate were measured.

In this research, performance measures, including throughput, time delay, and packet drop rate, are selected to measure the efficiency of the network under different circumstances. These metrics are important for evaluating the performance of deep learning-based clustering in the context of reliability, transmission time and system stability for the given data. To obtain accurate results for these metrics, we employed MATLAB as the main tool for simulation and analysis. The network environment was simulated with the help of MATLAB tools used for data processing and visualization to obtain and analyse the relevant performance data under laboratory conditions.

To start, we make some initial measurements with no clustering so that we have an idea of the performance metrics before any supporting frameworks add their overhead. We then perform retook measurements to determine the impact of network performance. Finally, we measured the throughput, time delay and packet drop rate for each case.

In this phase, measurement metrics were studied for various scenarios and node types. There was also a comparative study in which the results obtained for the proposed clustering approach were compared with those of the baseline (without any clustering) and standard clustering methods. In the first scenario, data transmission was originally performed without clustering technology. On the other hand, the second scenario, where data transmission was carried out by clustering technology, yielded fairly good results. The network topology in Figure 2 allows the host nodes to talk to one another to send data to the main node (base station), as shown by the orange color in Figure 2. The clustering is built into 4 clusters of nodes. Clusters are represented by brown nodes and send data from each cluster-to-cluster head.

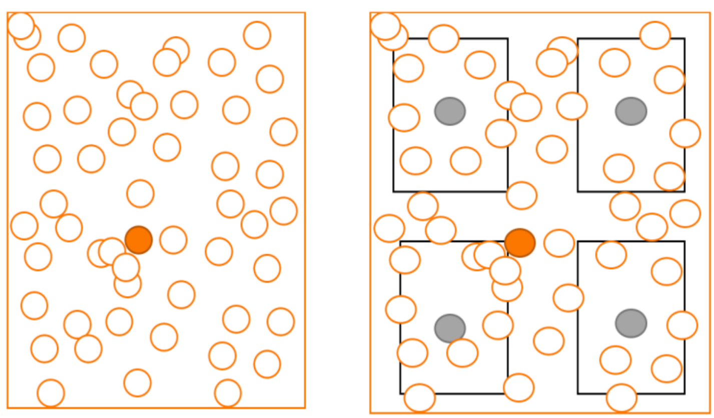

Fig. 2. Topology representation of the proposed clustering (right side) and the standard case (no clustering) on the left side

This model contains routing protocols such as AODV and follows the guidelines described in Table 1. As shown in Table 1, the nodes move randomly, with a speed of 10 m every 30 seconds. Initially, all nodes were linked to the base station without using a clustering approach, as shown in Figure 2 (left side). After that, the nodes were connected to four CHs located at the base station, and a cluster head was placed near where they centralized within each associated cluster, as shown on the right side of Figure 2. The host nodes move around the area but keep in touch with the cluster head, which is closer to them. The rectangular topography of the system pronounced the formation of four clusters; each corner was occupied by a cluster to increase coverage across the entire arena.

TABLE I. THE DELIVERY RATE FOR EACH CASE WITH A DIFFERENT NUMBER OF NODES

Host/Nodes	**D &CBPNN**	**D & No Cluster**
50	37.21	23.33
100	132.87	98.6
200	428.8	126.33

2.2 Optimized Deep Learning Clustering

The particle swarm optimization (PSO) algorithm can enhance the performance of a cascade back propagation neural network (CBPNN). In this context, applying the PSO algorithm can improve the CBPNN results [8]. Thus, through the use of a CBPNN, the PSO algorithm can optimize the weight and bias for a network and enhance its performance. Owing to the algorithm's innate supervised and unsupervised learning aspects of exploration and exploitation, which enable it to efficiently manoeuvre through the entire weight space, it searches for optimal solutions therein, thereby improving CBPNN strength in prediction lOP and generalization or predictability. Even though PSO iteratively attempts to find the optimum solution through interactions between particles, it only achieves slow convergence toward the global minimum because of an exhaustive search in high-dimensional space [15], [16]. Integrating the PSO algorithm into a CBPNN achieves a performance with greater accuracy.

Clustering results can then be evaluated by comparing the predicted cluster labels with some known ground-truth labels. The effectiveness of the clustering approach can be evaluated in terms of several metrics via different methods. Such as accuracy, energy efficiency and network lifetime, etc. Optimize the architecture and parameters of the neural network for better performance in clustering.

The packet delivery rate ($DRate$) is used to measure the performance of networking—a statistic that describes the percentage of transmitted packets measured separately for each network node. Equation (1) can be represented, and it expresses more information about determining the packet delivery rate:

$$DRate = \frac{X}{L} \times 100\% \qquad (1)$$

In this sense, L is the total number of packets that are transmitted through each node in the network; X is the subset of packets that successfully reach the destination station. The total number of dropped packets ($DRate$) is the sum of all these lost packets while transferring from perpetrator nodes to the destination nodes, as shown in Equation 2:

$$D = R - X \qquad (2)$$

In the given context, R denotes the entirety of the generated packets. Latency refers to the typical time it takes for a packet to travel from its source to its destination. It is measured in seconds, starting when the destination node receives the packet and confirms its successful arrival.

A well-known clustering protocol is the hybrid energy-efficient distributed (HEED) algorithm [8]. HEED uses a hybrid of residual energy and communication costs to select a cluster head to ensure the uniformity of the cluster distribution and to improve the network lifetime. However, the developed approach may be simpler and more widely distributed than HEED. However, it does not adjust because performance is dependent on the dynamic content and node mobility flows as is the case for CBPNN-based clustering.

Another relevant protocol is low-energy adaptive clustering hierarchy (LEACH) [1], which is a popular clustering algorithm in which the energy overheads are uniformly distributed among nodes with random rotations of cluster heads. Some alternative methods such as LEACH could provide a reasonable concern that enables enhancing, but it may not be as good as the CBPNN when considering the performance inconvenience of the network in managing homogeneous features between nodes and guaranteeing that packet drop is minimized with increasing network scale. The EEUC algorithm [2] uses an unequal clustering mechanism that forms clusters of different sizes depending on the distance from the BS. This approach can equalize the energy consumption of CHs; however, it is not expected to be as accurate in terms of throughput and delay optimization with CBPNN-based clustering.

With respect to routing protocols, we may also be interested in comparing RIPN with the gradient-based routing (GBR) protocol [3] and the energy-aware routing (EAR) protocol [4].. At the same time, it aims to direct data toward the base station via a gradient-based approach; EAR is based on energy-efficient routing that considers the energy available over nodes. Different packet delivery ratios, energy efficiencies, and scaling trade-offs can result from SIMD based on the CBPNN-implemented clustering with respect to these protocols.

3. RESULTS

In the no-clustering situation, as the number of nodes and the time delay increased, the number of dropped packets and packet drop rate increased. However, the introduction of 200 packets also slightly increased throughput because of the random mobility of nodes. Clustering approach based on the CBPNN (content-based probabilistic neural network). The results indicate that its performance is slightly better than that of both standard clustering and no-clustering cases. The throughput of the network increased to a considerable optimum level but with a reduced delay and packet drop rate. Moreover, the packet delivery rate is increased. The delivery rate for each node is shown in Figure 3.

Fig. 3. Graphical representation of the delivery rate for each case with a different number of nodes

A comparison of the drop rates in the pairwise and triple scenarios with different numbers of nodes (a zero tree is included at 20 Kbps) is shown in Table 2. The results demonstrate that there is significant variation in the drop rates achieved by using different configurations of nodes with the CBPNN-based clustering approach compared with a no-clustering scenario. The drop rates are much lower than those in the no-clustering scenario for the CBPNN. For example, when the number of nodes is 50 and if multiple rounds are considered in this simulation scenario (in the CBPNN method), then the drop rate is only 12.43; however, it can be as high as 1403 without clustering. This trend is observed as the number of nodes increases, in which case the CBPNN scenario always has a low drop rate compared with the no-clustering cases.

Table 2 also shows a 34.5% drop rate in the CBPNN scenario, whereas it reaches 95.15% in the no-clustering scenario, again considering at least 100 nodes. (n) This disparity reflects the efficiency of CBPNN-based clustering in reducing packet drop rates while improving network (network expansion) performance. The above figure further shows that the drop rate in the CBPNN scenario decreases to 89.4 for 200 nodes, which indicates that the proposed clustering approach yields a low drop even when the number of nodes increases. However, a greater drop rate of 116.4 is observed in the no-clustering situation. This proves that clustering indeed helps to limit packet loss in wireless sensor networks, as shown.

TABLE II. DROP RATE FOR EACH CASE WITH DIFFERENT NUMBERS OF NODES

Hosts/Nodes	DRate & CBPNN	DRate & No Cluster
50	12.43	1403
100	34.5	95.15
200	89.4	116.4

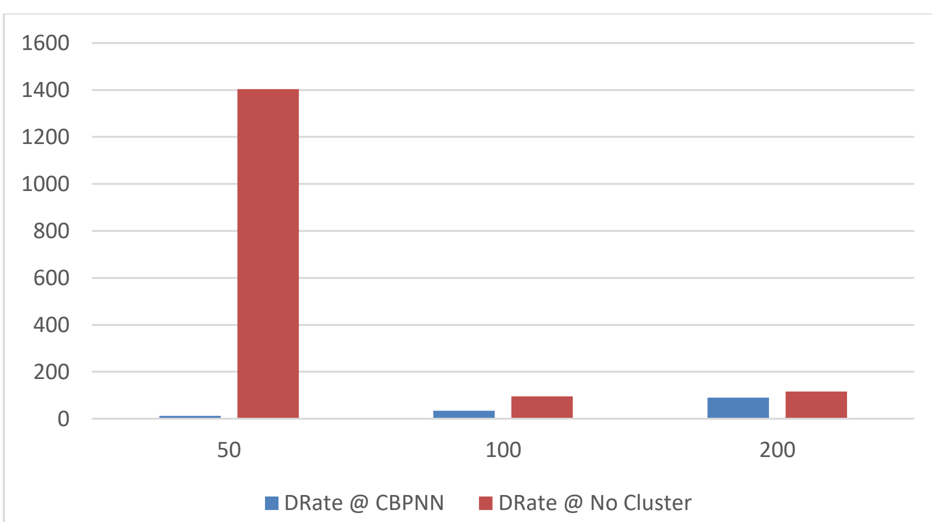

Fig. 4. Graphical representation of the drop rate for each case with a different number of nodes

The no-clustering scenario proved that the increase in nodes increased the time delay, packet drop rate, and dropped packets. Now, once we know that it works with 200 packets applied, clustering via the CBPNN achieves better results than do no clustering or standard clustering techniques. The throughput of the network increases to an optimal level, and the delay and packet drop rates decrease. In addition, the packet delivery rate has improved.

In terms of throughput, the proposed classifier-based clustering approach yielded significant enhancements in terms of throughput. This means that the network was able to have an average throughput of 132.87 Mbps with 50 nodes in the network, which increased to 428.8 Mbps when the number of nodes was scaled to 200 nodes. The delivery rate, one of the most important indicators of network performance, also increased with increasing node count. That is, for 50 nodes, the network had a delivery rate of 37.21%, which increased to 89.4% at 200 nodes. This trend shows that the deep learning-based classifier improved the communication paths since it was able to open new paths with the available number of nodes. This is why the changes that were observed in the experiments were deemed quite encouraging, especially with respect to the packet drop rate. In the case of 50 nodes, the drop rate for the clustering performed by the classifier was determined to be 12.43%, which is significantly lower than the 74.3% recorded in cases that are not clustered. When the node density was increased, the drop rate was maintained at a minimum of 34.5%, and 89.4% drops were also observed at 100 and 200 nodes, respectively. The proposed approach also improved the network latency, especially for larger node structures. For 50 nodes, the average latency was noted to be 1.2 seconds, and for 200 nodes, it was reduced to 1 second only through CBPNN clustering, indicating that it can handle a greater number of nodes without a high delay, as depicted in Table 3.

TABLE III. NETWORK LATENCY IN SECONDS

Number of Nodes	Latency (No Clustering)	Latency (CBPNN Clustering)
50	1.2	0.5
100	2.1	0.7
200	3.5	1.0

4. DISCUSSION

If there is no clustering as n increases, the delay time also increases, and the packet drop rate increases. This outcome is in line with what we may expect a WSN to behave when the node density reaches high levels, as an increased number of nodes will result in greater delays and packet losses due to collisions caused by contention for channel access[17]. However, a slightly higher throughput is achieved using 200 packets, possibly because of the random mobility of the nodes [18], [19]. Therefore, increasing the node density increases the packet delivery rate since there are more opportunities for nodes to communicate with each other.

In contrast, the CBPNN-based blustering achieves better performance than standard clustering and nonclustering. As a result, the throughput increased to the ideal state, and the delay and packet drop rates decreased. Second, the delivery rate for packets also improved. This is due to the CBPNN method proposed in our clustering scheme, which can adjust the network's dynamic behavior and intelligently choose optimal nodes for clustering according to their content popularity distribution and mobility patterns [18], [19]. If nodes with similar characteristics are clustered, it can reduce contests for channel access and packet collisions and hence improve network performance.

The results obtained in this study emphasize that clustering and node density should be considered when designing and optimizing WSNs. The proposed clustering mechanism using the CBPNN can increase the throughput delay and packet delivery ratio. This is an integral part, especially in applications that need to transmit real-time data.

The results show that the CBPNN-based clustering and no-clustering cases behave differently in terms of drop rates at different node configurations in the WSN. CBPNN-based clustering can effectively reduce the packet drop rate under different node densities. The CBPNN scheme results in significantly lower drop rates (in comparison with no clustering) as the network grows in size and even at high node counts, illustrating that the approach is capable of reducing packet losses with increasing network size. For example, for 50 nodes, the average drop rate was 12.43 in the CBPNN scenario, which is much lower than that in the no-clustering scenario, which has an average of 1403. In this respect, we observed a continuous trend of increasingly low drops as the node density increased, for which the drop rates were always dramatically lower in the CBPNN. Additionally, the drop rates decrease to 89.4 with 200 nodes, highlighting that the clustering scheme is able to maintain a low drop rate, although larger networks are used.

Notably, other traditional clustering methods, such as K-means [20] or hierarchical clustering, are not practically applicable because of their packet drop rates, especially in dynamic networks with dense nodes. Although these methods are intuitive and easy to scale, they may not be sufficient for efficiently addressing packet loss in large wireless scenarios, and more flexibility/sophistication can be exploited. Moreover, these methods are often based on geometric proximity, which may not capture the sophistication of edge relationships. which restrict them from realizing full network performance potential in content-aware applications.

To analyse the achieved network metrics, the increase in throughput is due to the classifier that adaptively modifies the clustering settings according to the nodes' behavior and traffic characteristics to optimize data forwarding and avoid network overcrowding. In real time, the approach minimized bottlenecks that usually arise in noncluster networks; hence, the throughput was considerably poor at each node density. The increase in the delivery rate substantiates the ability of the classifier to handle large node densities, whereby more packets are delivered to the intended nodes without loss or delay. However, this approach is likely to reach a point of optimal, where adding more nodes may lead to traffic or overhead. The consistent decrease in the value of packet loss can therefore be attributed to the classifier, which is able to adapt to changes in the network to ensure that the packets are forwarded through the best paths. However, the nonclustered network had higher drop rates than did the clustered network, especially as the number of nodes in the network increased, hence causing congestion and poor routing, which led to severe packet loss. An increase in latency is beneficial in scenarios where low latency is vital for real-time applications. The deep learning-based classifier uses the adaptive clustering technique, in which the clusters are rearranged dynamically to reduce the routing distance between the source and destination nodes.

In comparison, the LEACH, HEED and AODV routing protocols—unlike clustering approaches—are being proposed to address data routing in WSNs for efficient communication [21]. Although routing protocols play an important role in ensuring the delivery of data consistently, they are less likely to cope with packet drops as a result of network congestion and contention. Routing protocols are responsible for maintaining internode communication and intranode data forwarding strategies, unlike clustering approaches, which oversee the allocation of resource distributions within a cluster [22]. As a result, routing protocols can offer some extra advantages when used with clustering techniques to enhance network performance overall.

The results demonstrate that the CBPNN-based clustering method has great potential in minimizing the packet drop ratio for WSNs, especially in higher node density situations. To solve the problems of these high expression patterns, we propose a more effective solution that improves network performance and stability in optimization based on artificial machine learning technology implementation via a content-based clustering mechanism.

5. CONCLUSION

MANETs are central to short-range connectivity among hosts via a wireless medium. The major factors influencing the communication efficiency of these networks are related to the total number of network nodes and the amount of data transmitted. In this study, we evaluated the performance of routing protocols in clusters via scenarios one and two to understand the effectiveness of clustering on routing. Situations: 50, 100 and 200 nodes without clustering. We used cluster-based routing and formed 4 clusters by applying 50, 100 & 200 nodes. The base station node is very important to network coverage and is responsible for receiving information sent by host nodes. When the nodes are below this distance from the base station, they can talk directly to it. Otherwise, they create multihop connections through intermediate valid nodes above that threshold.

The deep learning-based classifier for adaptive clustering in mobile ad hoc networks (MANETs) yields better results for different parameters, such as throughput, delivery rate, packet drop rate, and latency. The results show that the classifier is able to adapt well to the current network conditions to form the best clusters and route data. This adaptive approach is much more effective than the conventional clustering and nonclustering approaches are, especially in the high-density node scenario. The applicability of the method, the possibility of changing parameters during the process, and the ability to scale it make it plausible for usage in different practical tasks to improve MANET performance.

In terms of implementation, the classifier-based clustering method provides significant advantages for practical application of the concept in real-world networks. The first benefit is its effectiveness in minimizing packet loss and enhancing delivery rates in dynamic, large-scale MANETs; the application of this protocol is ideal in environments that require a high degree of reliability, such as military, disaster relief and real-time data acquisition in remote locations. Additionally, its real-time reactivity guarantees that it can properly address unpredictable node behavior and network conditions, making it stable and energy effective for complex and highly mobile networks. This approach reduces latency and ensures that the data transmission is always constant with increasing network density and traffic.

However, this study has several limitations. First, the simulations were performed under certain node density and mobility scenarios, which deviate from real-world scenarios. Some of the constraints include environmental interference, high node mobility and variation in power levels, which were not explored deeply, thus restricting the generalizability of the results. However, the first limitation is the computational complexity, which is related to the real-time updates of the clustering in very large-scale networks, which could be challenging since the deep learning model needs a vast amount of computational power to learn and adapt to the dynamics of the network constantly.

This study can be further developed for research in the future by incorporating research efforts into how energy-aware algorithms can be incorporated into the classifier model to potentially reduce energy usage, especially among the energy-limited nodes in WSNs. Second, the proposed approach should be tested in a real environment by incorporating the interference, node failure and extreme mobility patterns of nodes. This would provide a better understanding of the model's capability in various fields and thus enhance its efficiency. Finally, examining the integration of deep learning-based clustering with enhanced routing algorithms may provide a more extensive solution for enhancing both intracluster communication and intercluster routing in MANETs and other wireless network classifications.

Conflicts of interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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