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Original Article

A Novel Manet Based on Fuzzy's Extreme Machine Learning

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Abstract - A wireless network with several peer nodes is known as a Mobile Ad-hoc Network (MANET). One of the largest barriers to growing multicast routing protocols in ad-hoc networks is the confined battery existence of cell nodes. The multicast routing technology can dramatically improve the MANET network's availability. This protocol's goal is to shorten the MANET network lifetime and energy usage. A novel, Manet-based Fuzzy Extreme Machine Learning (MFE-ML) approach has been put forth in this study to solve these problems. Two phases make up the whole process like, Cluster Head (CH) selection and routing. Fuzzy ELM is used in the first phase to choose the CHs. Monte Carlo simulation is used in the second phase to execute routing depending on variables such as residual energy, node order, node distance, and CH order. The effectiveness of the proposed MFE-ML technique is evaluated using a number of metrics, such as community lifetime, common cease-to-cease delay, packet transit speed, throughput, and standardization data use on energy. The result of simulations shows that MFE-ML is an efficient solution for routing in the networks. Compared to GKCA, RRCST, and EBCH, the MFE-ML technique extended the network lifetime by 17.24%, 19.45%, and 22.34%, respectively.

Keywords - MANET, Clustering, Cluster head selection, Monte-Carlo simulation, Fuzzy extreme learning machine.

1. Introduction

A network of communicating nodes or devices known as a Mobile Ad-hoc Network (MANET) is one that aims to communicate but does not rely on existing protocols [1]. A MANET does not require network infrastructure or centralized management for mobile nodes to connect with one another [2]. Mobile nodes do not have authoritarian systems like access points or switched telephone networks [3].

While wireless communication interfaces have sufficient power to transmit, it may take several hops for a node to share data with another node across the network. Dynamically identifying and locating other nodes in a MANET is accomplished by configuring accessible linkages among nodes [4]. Android nodes are connected to one another by network signals to create a self-contained network that can take any topology [5]. In order to address the overhead and scalability issues, MANETs may occasionally be divided into smaller sub-networks (i.e., clusters) utilizing a variety of clustering algorithms based on a range of influencing factors, including available energy, mobility speed, and so on [6]. Multicast protocol design is challenging due to power restrictions, bandwidth limitations, and mobile hosts [7].

Limited bandwidth, restricted power, and end-to-end delay are the major causes of the necessity for an optimal and quick routing algorithm [8]. Manet-based Fuzzy Extreme Machine Learning (MFEML) based on MANET has been proposed to overcome these difficulties. The major contribution of the suggested approach is as follows:

- The aim of this protocol is to minimize the energy consumption and network lifetime of the Mobile Ad-hoc Network.
- The two steps of the proposed MFE-ML technique are cluster head selection and routing.
- Using Fuzzy ELM in the first phase, the CH is chosen, and routing is done in the second phase using the Monte-Carlo Simulation based on the parameters such as residual energy, node degree, the distance of the node and CH degree.
- The proposed MFE-ML approach results in a high throughput, network lifetime, Average End-to-End delay, packet delivery ratio, and low energy consumption.

The rest of this work was prearranged into 4 sections: The following section of this research is demonstrated. Section 2 describes the literature review. Section 3 presented the proposed MEF-ML, along with an explanation and the related algorithm. Section 4 includes the performance results and their analysis. Conclusions and future work are included in Section 5.

2. Literature Survey

One of the biggest restrictions on creating multicast routing protocols in ad hoc networks is the limited battery life of mobile nodes. The multicast routing technology can dramatically improve the MANET network's availability. The aim of this protocol is to minimize the energy consumption and network lifetime of the Mobile Ad-hoc Network. In 2019, Shadi Abpeykar, and Mehdi Ghatee [9] developed a neural tree created for high-dimensional data classification., employing peer-to-peer and server-to-client knowledge transfer techniques. With the least amount of inner redundancy, the suggested approach defines a few highly relevant attribute clusters that are not disjoint; the models use a fuzzy aggregation method to modify the rules' level of certainty.

In 2020 Sindhanaiselvan et al. [10] developed a clustering approach to decrease power consumption during communication from source to destination. The EBCH approach is simulated in MATLAB and compared to the ENB and CPN algorithms, resulting in a longer network lifetime and reduced power usage. However, EBCH technology has a relatively limited network lifespan. In 2020 Ying Song et al. [11] proposed a graph kernel-based clustering algorithm in MANET. The GKCA method is simulated using Network Simulation Software (NS2). It provides an efficient method for estimating and evaluating the stability of cluster heads in dynamic cellular networks. However, the GKCA technique needs to be improved by supporting nodes with limited mobility.

In 2020, Yonghe chue et al. [12] developed a Fuzzy ELM for class based on feature space. Extreme Learning Machine (ELM) has been widely employed in the field of pattern accuracy as a competitive machine learning method due to its straightforward theory and straightforward implementation. Researchers have devised related research techniques to account for noise and outlier data. In 2021 Muruganandam and Arokia Renjit [13] suggested a novel dependable real-time clustering and secure transmission technique for MANET QoS advancement. The RRCST approach enhances clustering performance as well as throughput and malicious node identification. For 200 nodes, the suggested RRCST algorithm achieves 97% clustering accuracy. RRCST technology, on the other hand, consumes a lot of energy.

In 2022, Deepak Kumar Jain et al. [14] proposed creating a traffic and energy management estimation method using fuzzy logic for cyber-physical systems. Cyber-Physical Systems (CPS) is a heterogeneous effort connecting cyber and physical vectors. The power system and TFP methods are the two main components of the FLEM-TFP strategy that is put out here.

However, some relevant research has been conducted to minimize power consumption and maintain the reliability of MANET networks. We presented an MFE-ML approach in this study to reduce power consumption, transmission latency, and network robustness. Trust management, cluster routing, and head election are the three phases in the suggested MFE-ML approach.

3. Proposed MFE-ML Methodology

A novel Manet-based Fuzzy Extreme Machine Learning (MFE-ML) approach has been proposed in this study. Two phases make up the whole process which are the CH selection and routing. In the first phase, the Fuzzy-ELM is used for CH selection and routing is done in the second phase using the Monte-Carlo Simulation based on the parameters such as residual energy, node degree, the distance of the node and CH degree. Figure 1 shows the overall structure of the proposed MFE-ML technique.

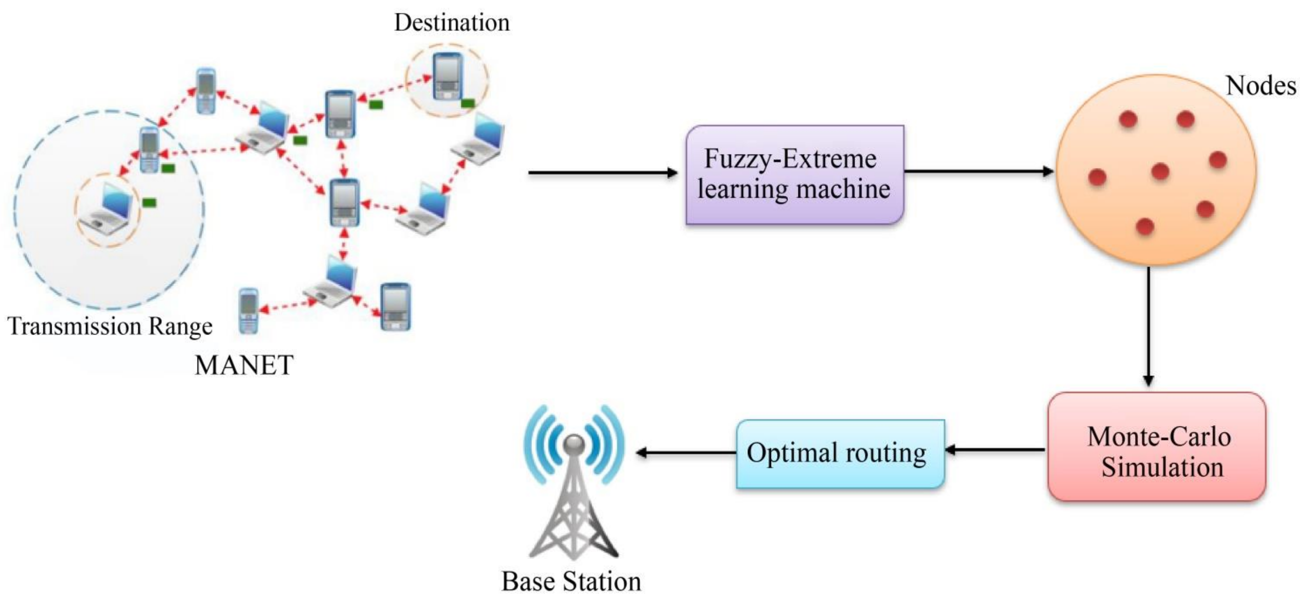

Fig. 1 Overall framework for proposed MFE-ML architectures

3.1. Fuzzy- Extreme Learning Machine

ELM focuses on extended SLFNs, in which concealed layer is tuned automatically and may not resemble neurons. The output weights of ELM are derived analytically, and all of the hidden node values are produced at random. ELM tends to both reach and maintain the least training error and output weight norm, in contrast to conventional learning models:

$$\text{Minimize:}\sum_{i=1}^{N} ||\beta h(x_i) \text{ -} t_i \quad \text{and Minimize:}||\beta|| \tag{1}$$

Where β_i is the output weight, h(x_i) is an output vector. input x_i *and* $t_,$ is the label to x_i. The minimal norm least square method is used in the implementation of ELM:

$$\beta = H \dotplus T \tag{2}$$

ELM performs similarly for class when compared to SVM and teaches far faster. Unfortunately, the majority of useful uses include weighted classification issues, which the classic ELM is unable to handle. To solve this issue, fuzzy ELM is suggested in this letter.

$$(X_1, t_1, s_1), \ldots, (X_N, t_N, s_N) \tag{3}$$

Minimize: $L_{FELM} = 1\backslash 2\ ||\beta||^2 + C1\backslash 2 \sum_{i=1}^{N} s_i\ ||\xi_i||^2$

$$h(X_i)\beta = t_i^T - \xi_i^T, \{\}\ i = 1, \ldots N \tag{4}$$

Thus, the inputs with various fuzzy arrays might help in various ways to the development of the output weights β. Then, the output function of the FELM classifier is

$$F(x) = h(x)\beta = h(x)H^T\left(\frac{S}{C} + HH^T\right)^{-1}T \tag{5}$$

$$Label(X) = arg\ max\ f_j(X) \quad j\epsilon\{1, \ldots, n\} \tag{6}$$

FELM only takes one output node and the starting from planning for binary classification issues. It is used to identify the output node with the highest output value by its index number as the projected class label of the following characteristics for m-class scenarios. The fuzzy matrix S can also be altered easily in accordance with various purposes to address various issues.

3.2. Monte-Carlo Simulation

The main approach in subsurface economics and the fracking industry for assessing the error in flow and transfer calculations deriving from uncertain aquifer layout, hydrologic variables, and forcing terms is known as Monte Carlo (MC) simulation. A few synthetic conclusions of the relevant random variables are used as the basis for MC simulations, which are used to test the accuracy of approximation moment-based models for groundwater flow and transport.

$$Pr\left[K_{n-t_{n-1}}\left(1-\frac{\alpha}{2}\right)\frac{s_n}{\sqrt{\eta}} \leq \mu \leq K_n + t_{n-1}\left(1-\frac{\alpha}{2}\right)\frac{s_n}{\sqrt{\eta}}\right] = 1-\alpha \tag{7}$$

$$Pr\left[K_{n-\alpha}\frac{\sigma}{\sqrt{\eta}} \leq \mu \leq k_{n+\alpha}\frac{\sigma}{\sqrt{\eta}}\right] \geq 1-\frac{1}{\alpha^2} \tag{8}$$

In this case, the likelihood that the process mean value is contained within the confidence interval surrounding the sample mean $K_n$is underestimated by $(1-1/\alpha^2)$. Equations 3 and 4 demonstrate that for any given probability value, the confidence intervals' amplitude-scaling factor is $Sn/\sqrt{\eta}$, an estimator for $\sigma/\sqrt{\eta}$. They may easily be used to assess the Convergence of Monte Carlo findings. The biases of these estimates can be assessed as a function of the actual values of the sample moments of tension, the size of the sample or the number of processes implementations because MC realizations are used to calculate ensemble moments.

4. Result and Discussion

This part discusses the proposed Manet-based Fuzzy Extreme Machine Learning (MFE-ML) multicast routing. The Network Simulation Software (NS2), which has an Intel core processor and 4 GB of RAM, was selected for implementation. The effectiveness of different routing protocols for MANET is evaluated and contrasted. This section assesses the effectiveness of our proposed (MFE-ML) protocol.

4.1. Performance Metrics

The proposed model's effectiveness was evaluated using the following variables:

4.1.1. Energy Consumption

Energy consumption is the overall amount of energy the device needs while packets are being transmitted.

$$E_c = \sum_{x=1}^{N} E_{x,P} \quad (9)$$

Here, $E_{x,P}$ is a representation of Network X's overall energy consumption after P rounds of collecting information, and N stands for the number of networks.

4.1.2. Throughput

The term "flow" refers to the total number of packets that are successfully delivered to the node target over a period of time. The range of the calculation is 0 to 100 bits per second. Less nodes will improve the performance of the proposed system since they will provide high throughput, whereas more nodes will lower overall data rates and speed.

4.1.3. Packet Delivery Ratio

Packet delivery is defined as the proportion of total packets produced at a given node over the course of a certain time period to the total packets lost over the same time. It is calculated as a percentage with a range of 0 to 100. Inversely correlated with system performance is the typical packet loss ratio. The suggested system works well with fewer nodes; however, as the number of nodes increases, the average packet loss ratio of the proposed system causes it to function poorly.

4.1.4. Network Lifetime

One of the most important components of designing protocols that take energy into account is starting the protocol until the first node dies as a result of battery weariness.

4.2. Comparative Analysis

This section includes simulations to evaluate the effectiveness of the suggested MFE-ML methodology. Comparisons are made between the proposed protocol and the GKCA[11], RRCST [13], and EBCH [14] protocols. Many measures, including network lifetime, latency, average end-to-end delay, throughput, detection ratio, and package delivery ratio, are used to assess the MFE-ML protocol.

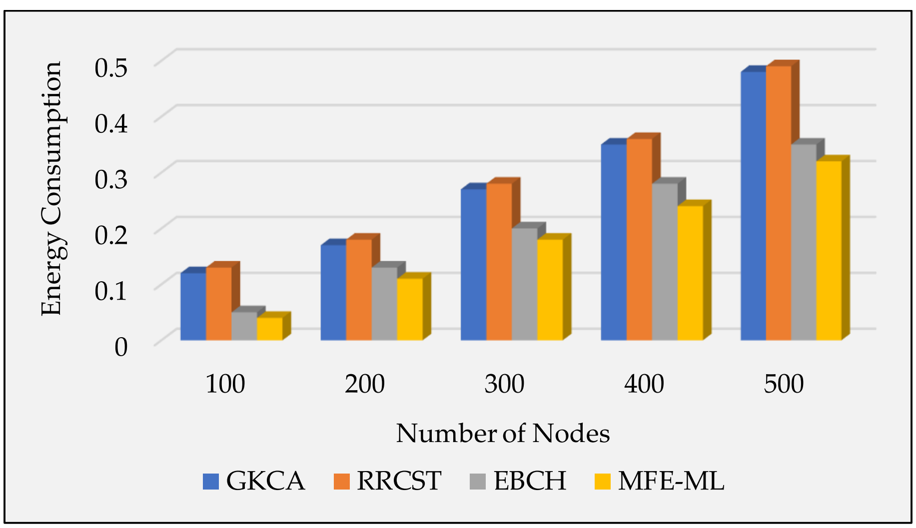

Fig. 2 Energy consumption vs Number of nodes

The comparison of the proposed MFE-ML with the existing techniques, such as GKCA, RRCST and EBCH, in the case of energy consumption, is shown in Figure 2. Figure 2 shows that when compared to the following conventional approaches, the proposed MFE-ML consumes less energy.

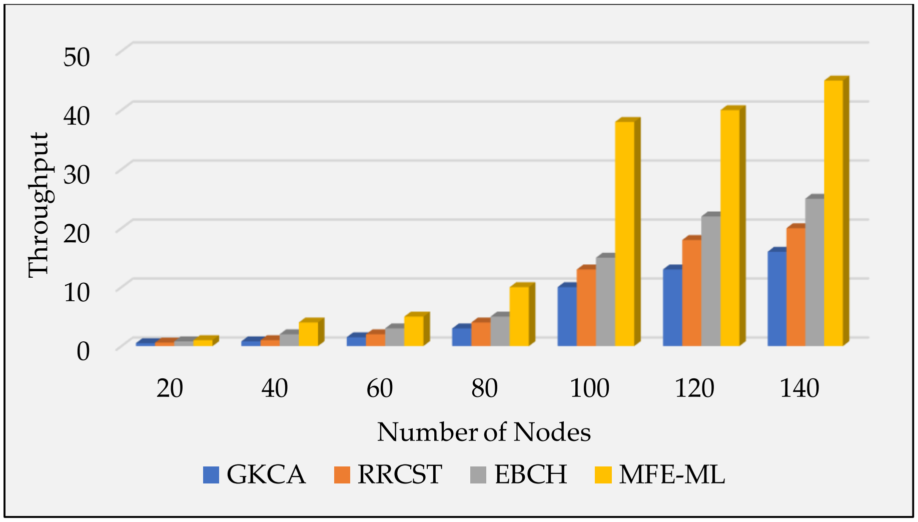

Fig. 3 Throughput vs Number of nodes

Figure 3 shows throughput performance results for both the preferred technology and the current technology. The proposed MFE-ML achieves better throughput results than the existing GKCA, RRCST and EBCH techniques.

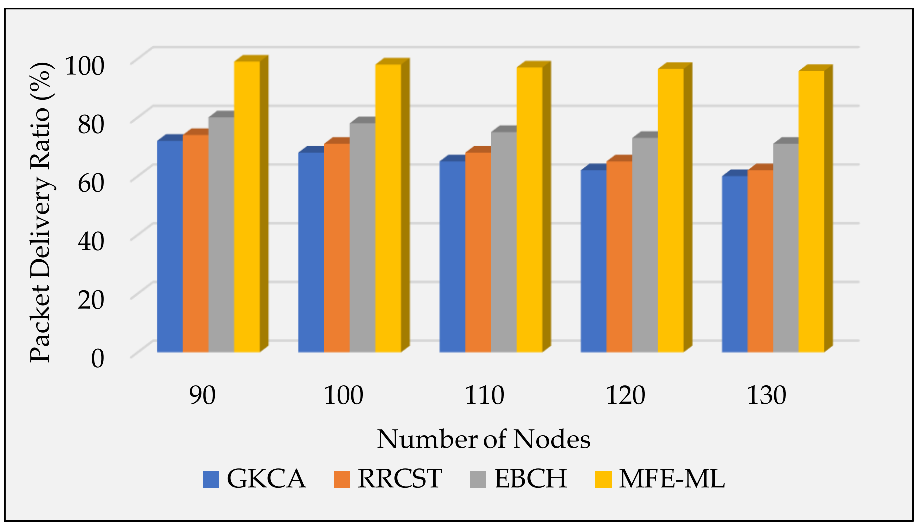

Fig. 4 Packet delivery ratio vs Number of nodes

The comparison of the proposed MFE-ML with the existing techniques, such as GKCA, RRCST and EBCH, in the case of packet delivery ratio, is shown in Figure 4. Figure 4 shows that the packet delivery ratio is very high in the proposed MFE-ML method compared to the existing methods.

In Figure 5, the network lifetime is shown in relation to the proposed and existing models. While the EBCH model typically has a network life span of 20.0% and the RRCST model typically has a network lifetime of 39.0%, the average network lifetime compared to the GKCA model is 17.5%. Having a better overall network lifetime of 45.70% for the proposed model.

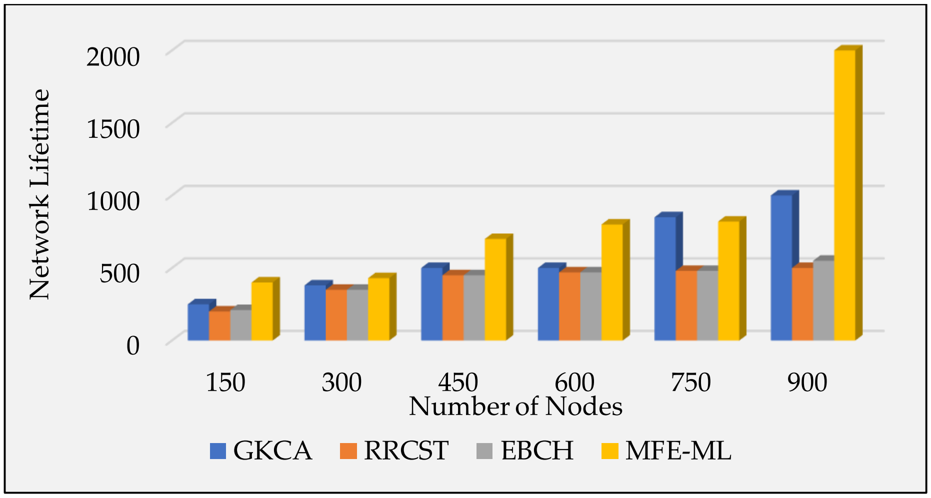

Fig. 5 Network lifetime vs Number of nodes

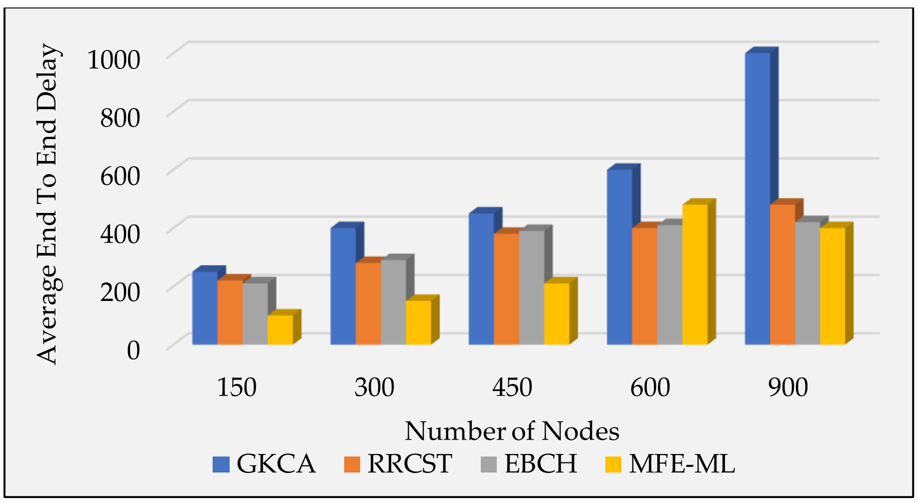

Fig. 6 Average end-to-end delay Vs Number of nodes

The three approaches' routines' end-to-end delays are contrasted in Figure 6. As a result of each EBCH node adjusting the pool for a certain time period based on the change in complexity in the preceding period, the results demonstrate that GKCA has a significant end-to-end latency. Moreover, as the number of nodes rises, the GKCA delay increases. Because each node holds onto the packet, adding more nodes causes more latency. End-to-end delays for RRCST, EBCH, and GKCA are similar.

5. Conclusion and Future work

A unique Manet-based Fuzzy Extreme Machine Learning (MFEML) method has been proposed in this study. Two phases make up the whole process, such as the CH selection and routing. Fuzzy-ELM is utilized in the first stage to choose the cluster leader, and Monte Carlo simulation is used in the second stage to choose the best path based on factors such as residual energy, knot degree, distance from the knot, and CH degree. The proposed MFEML approach's efficiency is assessed using several variables, including throughput, network lifetime, typical end-to-end latency, power consumption, and packet delivery rate. The result of simulations shows that MFEML is an efficient solution for CH selection and routing in the networks. Using the proposed MFEML method, the network's lifetime increased by 17.24%, 19.45% and 22.34%, respectively, compared to GKCA, RRCST and EBCH. Future studies will concentrate on developing efficient monitoring methods to lower transmission uncertainty in open wireless situations.

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