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Adaptive Neuro-Fuzzy Inference System Based On-Demand Fault Tolerant Routing Protocol (ANFIS-ODFTR) for MANETs

Suneel Kumar Duvvuri
Department of Computer Science, Government College (Autonomous), Rajahmundry, Andhra Pradesh, India
suneelcs@gcrjy.ac.in

S. Ramakrishna
Department of Computer Science, S V University, Tirupati, Andhra Pradesh, India
drsramakrishna@yahoo.com

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Abstract – Due to adverse characteristics such as open medium, recurrent restructuring of paths, power constraints, and high mobility of MANETs, the nodes and links failed frequently. These failures increase the control overhead because of the tedious route discovery process. Thereby the performance of the network diminished drastically. Devising an efficient on-demand routing protocol with fault tolerance is a challenging task. Detecting and removal of these faulty nodes during data transmission without affecting the communication flow is very critical because of the unavailability of path information. The research challenge of designing the effective fault tolerant routing protocol for MANET is addressed in this study. An Adaptive Neuro-Fuzzy Inference System was utilized to create a fault-tolerant routing system. The fault tolerant routing protocols based on numerical estimation are discussed. Simulation results have attested that the suggested approach considerably boosts the Packet Delivery Ratio while lowering the Routing Overhead.

Index Terms – MANET, Fuzzy Inference System, ANFIS, Hybrid Neural Network, ANN, Fault Tolerance, AODV, RSSI.

1. INTRODUCTION

Wireless Mobile Ad hoc Networks (MANET) are auto-configurable, decentralized, flexible, and randomly movable group of nodes that can interconnect with each other without access points. These attributes make them highly adaptable networks for brisk use in sensitive and tough environments. The most significant applications of Mobile Ad hoc Networks are military operations and civil, emergency and rescue operations. Each Node in MANET has different potentials such as transmit, receive, and also route data packets which are designated for other destinations. The Nodes in MANETs have high mobility so, they can be added and detached from the MANETs at any instance. Due to their exceptional characteristics, the MANETs are exposed to many challenges such as energy conservation, the need for complex routing algorithms to handle the dynamic topology, Faulty nodes detection, and isolation, security, etc. The major challenge is to create a highly reliable routing system which can cope up with faulty nodes in the network.

There were several types of routing protocols for MANETs, which can be cataloged into three main classes such as reactive, proactive, and hybrid protocols. The reactive protocols are on-demand routing protocols in which the sender node commences a routing path discovery by sending Route Request Packets to neighbour nodes in order to determine the best feasible path for the packet to arrive at the destination. Each member in the network has a routing table or cache of the routes that they can take to reach other nodes in the network, such that whenever a data packet is transmitted, their next hop is determined using the information in the routing table/cache. Ad-hoc On-Demand Distance Vector (AODV) [1] and Dynamic Source Routing (DSR) [2] are two reactive routing techniques, those adopt different procedures to identify the best feasible routes in the topology and maintain routing tables up to date. In contrast, the Proactive Routing Protocols like Destination-Sequence Distance-Vector (DSDV) [3] and Optimized Link State Routing (OLSR) [4] are not required to initiate the route discovery process but involved an exchange of complete routing tables on a regular basis to retain the routing table updated, which requires a large amount of data transmission.

One of the major challenges with the Routing protocol devise is we need to use the least control messages like Route Request (RREQs), Route Reply (RREPs), Route Error (RERRs). However, existing reactive protocols like AODV and DSR employ a large number of control packets during the route discovery and maintenance stages. Because of this over forwarding these packets increases routing overhead thus the packet delivery ratio can be decreased. Furthermore, after each link disconnection, the previous node will send an RERR control message to the origin node, informing it about the link interruption. In the course of action, the origin node instigate the new route detection process by broadcasting the RREQ control packets to the neighbor nodes, again overall control overhead increased in the network thus the packet delivery ratio decreased subsequently. And also the nodes which are actively taking part in routing at one point of time may frail in the due course of time due to energy constraints, packet loss as a result of congestion, Transmission errors, Link and route breakages, noise due to wireless medium. To guarantee the reliability, a "tolerant" procedure should be integrated into the routing protocol. Creating a stable fault tolerant routing path is a fundamental problem to be addressed in the MANETs. The main motivation for this research work is to attain the fault tolerance route by maintain reliability and balancing the tradeoffs of the MANETs.

The proposed protocol addresses the failure issues by creating an abstraction on AODV to reduce the number of rebroadcast requests by updating only the fresh neighbors in the routing tables of each node using Received Signal Strength Indicator (RSSI) [5]. It is an ideal measurement that ensures that the wireless channel should keep only the new neighbor information in every node. As well as, every node in the network will also require information on energy constraints, such as the amount of energy necessary for computing and the amount of energy utilized during communication, etc. The nodes must periodically examine their existing energy level, and when it goes below the certain level (threshold) value, they must exit the network and refrain from participating in the routing process by forwarding RREQ packets to build the path. As an outcome, the nodes with energy levels lower than the threshold would be excluded from routing tables. By eliminating the lower energy nodes, frequent link crashes and communication breakdowns can be evaded in the network.

Because of the rapid mobility of nodes in the MANET, it is very intricate to identify the routing changes, Link Expiry Time (LET), and low energy nodes. Within no time, the nodes have to calculate their distance with their neighbor nodes, speed variations in order to obtain the link expiry time. The Link Expiry Time and Node Energy monitoring impart robust path stability from sender to receiver transmissions.

An Adaptive Neuro-Fuzzy Inference System [6] based model on AODV is created in this research to enable fault tolerant routing. The proposed protocol's main goal is to lower the broadcasting of the Control messages; to achieve the fault tolerance by calculating the next-hop node distances using RSSI, path stability, Link Expiry Time, Node Energy Monitoring to avoid link failures. In this model, the network topology is maintained by the local nodes without propagating the RERR messages throughout the network. In addition the energy altitudes of each neighbor node can be examined to circumvent link failures and the estimate result of the neuro-fuzzy inference system being used to construct a strong path that eliminates the recurrent link disconnections thus the control overhead was minimized in the network.

The remainder of the article is organized as follows: The second section discusses the Literature Review in reference to past investigations. Section 3 outlined the Adaptive Neuro-Fuzzy Inference System (ANFIS). Section 4 describes the recommended protocol exploited in this work. Performance Analysis through Simulation is provided in Section 5 and to conclude, section 6 gives the Conclusion and Future Scope.

2. LITERATURE SURVEY

Nisha Chaudhary et.al [9] conducted research on ways to tolerate faults on best-optimized paths to route packets. To achieve maximum energy efficiency, every path has to have a signal intensity threshold. To prevent packets losses as a result of a link breakdown, route recognition and route management are monitored continuously. Extensive research into existing energy-saving protocols concludes that signal threshold plays an important role in a stable path. They have shown that the energy-based route selection as the parameter to achieve fault tolerant routes in the network.

Fault tolerant QoS Routing Protocol (FTQRP) was proposed by Ravichandra and Chandrasekar Reddy [10] to obtain a high-tolerance route when there are Faulty nodes in the control area. If any route was broken other routes were found and packets were transferred through that different route to improve packet delivery rate. To achieve fault tolerance, an alternative route was selected from the backup routing table which was continuously maintained with Hybrid Automatic repeat request. They have compared the protocol with their another proposed algorithm, that is an Energy efficient QoS based routing using Genetic Algorithm (GA) (GAEEQR) and provided that, the fault tolerance rate is better with the FTQRP than with the genetic algorithm technique, and it outperforms GAEEQR with respect to packet delivery rate, power consumption, end-to-end delay, and throughput. The control overhead was not mitigated as related to the standard AODV protocol.

Senthil et al. [11] used the fuzzy logic method to devise energy-efficient QoS routing to evaluate link durability. It's a cross-layer model [7] in which physical layer characteristics may be employed to compute the signal-to-interference-plus-noise ratio (SNR) and the data link layer can estimate neighbour positions and back-off times. The data transmission rate was estimated to determine the packet transmission status. Multiple paths between sender and recipient can be identified using source routing and adaptable ad hoc on-demand multi - path distance vector (AOMDV). The Fuzzy Logic technique is employed to select most advantageous

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routes. Link termination time (LET), Link Received Signal Strength (LRSS), Link Packet Error Rate (LPER) and Probable Link Reliable Time (PLRT) are inputs to the fuzzy engine, and the route selection probability is determined as an output based on the fuzzy rules' results. They evaluated the protocol against by the CLM-LAR (cross-layer metric-based Location Aided Routing) protocol and discovered that the completed version had a higher packet delivery ratio and consumes less energy. Control overhead and end-to-end delays still need to be considered.

Fatemeh Tavakoli et.al [12] proposed a MANET error-tolerant algorithm. Through redundancy in this approach, network error tolerance has been successfully improved. Initially, backup routes and backup nodes have been selected based on reputational characteristics that were forecasted. The principal path between each source and destination has been anticipated, and fault tolerant routing will be implemented that once backup node collection gets completed. This algorithm is an abstraction of DSR protocol and be evidence for the better performance for Limited number of Nodes with low mobility in the network.

Gaurav singal et al. [13] created an integrated link-based multicast routing technique with multiple constraints while keeping Quality of Service (QoS) metrics in mind in order to get better results and increase network bandwidth efficiency. The link stability feature is used to calculate the number of steady nodes within the network. The authors employed the mesh-based route idea to preserve mesh connections while ignoring link failure. In their algorithm, Gopal Singh et al. [14] proposed the link expiry (LET) as an extent as the time till an unbroken connection. This parameter is one of the key parameter to the fuzzy rule engine to develop a fault tolerant touting protocol considered in this paper.

Sakthidasan Sankaran et.al [15] developed a novel secure neighbor selection algorithm with the integration of recurrent reward-based learning that accede to the benefits of intelligent machine learning approach and conventional routing for categorizing the status of nodes based on their communication mode.

Xin Ming Zhang et al. [16] proposed various neuro-fuzzy frameworks for rule generation to assess signal strength while two mobile nodes are nearer to each other and to forecast future distance after two nodes leave each other and the total of each and every hop distance of the earlier path to determine node pair distance. The suggested protocol Estimated Distance Based routing protocol (EDRP) calculates the Distance using Received Signal Strength and this protocol confirms that the decrease in the Control Overhead when compared to AODV.

B. H. Khudayer et al. [17] proposed two novel approaches to improving reactive source routing protocols: the ZRDM (Zone-Based Route Discovery Mechanism) and LFPM (Link Failure Prediction Mechanism). ZRDM tried to organize RREQ message floods, whereas LFPM aimed to eliminate route breaks induced by node mobility.

A. Bhardwaj and H. El-Ocla [18] devised AOMDV with FFn, a Genetic Algorithm (GA) technique to finding the best feasible route in the multipath routing protocol AOMDV [8].

Misra et al. [19] envisioned a Fault-tolerant routing Approach Based on Learning Automata (LAF TRA) for selecting optimized paths among multiple paths having faulty nodes. The basic idea behind using learning automata is to gain knowledge from the environment. In this protocol, an automaton (a self-learning machine code) is sited in every node that will monitor the traffic flow through that node. The learning process takes appropriate actions based on the network's response feedback. The automaton continuously gains the healthiness of its neighbor nodes. Before forwarding the packet each node itself decides which neighbor to be picked to forward the packet to achieve the highest packet delivery ratio. At the time of the learning process, each node computes the goodness value of the path using the responses from the other nodes. The response from the node will be sent through an Acknowledgement. The Simulation results demonstrated that this mechanism is satisfactory in all aspects except increases the energy consumption.

The studies reveal that a hybrid mechanism is required to balance the quality tradeoffs of MANETs. The main objective of this research study is to build a fault tolerant routing protocol that reduces the control overhead by considering RSSI, path stability, Link Expiration Time, Node Energy Monitoring as the fuzzy parameters to balance all the quality parameters of the MANETs.

3. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

Jung pioneered the Adaptive Neuro-Fuzzy Inference System method in 1993 [20]. ANFIS is a straightforward data acquisition module that employs Fuzzy Logic to convert given inputs into a preferred outcome via streamlined and connected neural network computational components and informational links that are induced to transform the numerous mathematical input values into an outcome.

ANFIS offers the features of dual learning algorithm approaches by combining the effectiveness of two machine learning approaches, such as the Fuzzy Logic’s qualitative approach and the adaptive capabilities of neural networks. [21]. ANFIS configures Fuzzy Inference System (FIS) parameters by utilizing Neural Network learning techniques. By combining the modeling function of abstract thinking and the learning capability of the Artificial Neural Network (ANN), a series of rules immaculately conceived from the experimental observations. ANFIS uses blended

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learning to discover the optimum allocation of membership activities/functions by mediating the link between the input and output processes. It is based on Takagi and Sugeno's [22] fuzzy "if... then" rules. The model's architecture consists of five layers, each with several nodes. (see Figure 1).

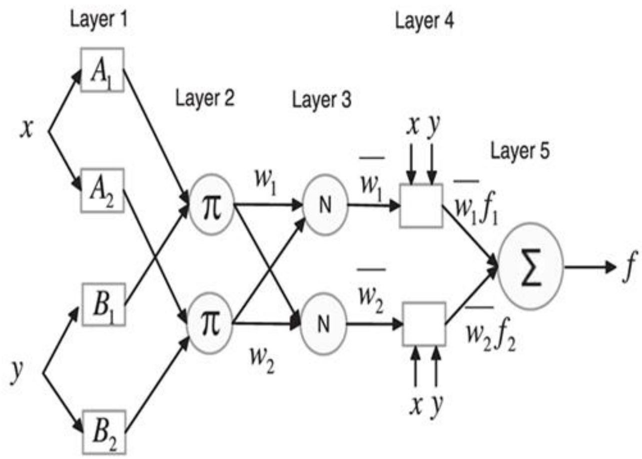

Figure 1 General Architecture of ANFIS

Every output membership function can be formed with different rules. The total set of rules as well as the overall number of membership functions must be equal. Two fuzzy inference rules are considered in the first-order Sugeno approach are:

Rule 1: **IF** x is A_1 **AND** y is B_1 , **THEN** $f_1=p_1x+q_1y+r_1$.

Rule 2: **IF** x is A_2 **AND** y is B_2 , **THEN** $f_2=p_2x+q_2y+r_2$.

Where x and y are the inputs, A_1, A_2, B_1, B_2 are the fuzzy sets, $p_1, q_1, r_1, p_2, q_2, r_2$ are the training parameters adjusted during the training process and f_1, f_2 are the outputs within the fuzzy region summarized by that of the fuzzy rule.

ANFIS engages a hybrid learning algorithm based on method of Least Squares and gradient descent [23]. During the forward iteration, the node's output advances up to Layer 4, and the resulting parameters are calculated using least-squares. In the backward iteration, the error signals spread rearward, and the system parameters are adjusted with gradient descendent.

4. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM BASED ON-DEMAND FAULT TOLERANT ROUTING PROTOCOL (ANFIS-ODFTR)

The Proposed protocol adapted on-demand protocol AODV and supplemented with fault tolerant capabilities using ANFIS. The general AODV sequence for Route discovery and Maintenance was modified with Neuro fuzzy adaptive learning. Figure 2 depicts the AODV sequence diagram.

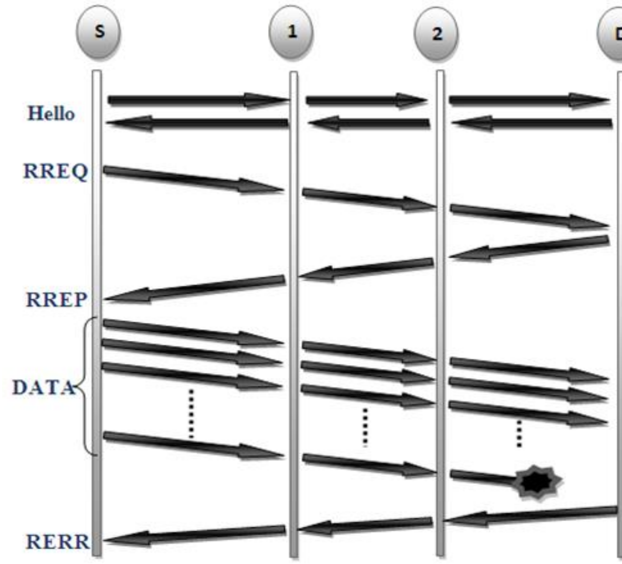

Figure 2 Sequence Diagram of AODV Routing Protocol

ANFIS-ODFTR protocol uses Received Signal Strength Indicator (RSSI) to update only fresh neighbors in the routing table after broadcasting the Hello Packets to one-hop neighbors. Also, Link Expiry Time (γ) will be calculated to obtain an accurate Path Stability Factor (α). To reduce the number of faulty network nodes caused by energy constraints, an energy threshold value (e*) will be calculated by each node and the nodes whose energy levels fall below e* will be self-isolated from the route discovery process by rejecting the Route Request packets. Hence lower energy nodes will be restricted to participate in the live routing path. The best optimal path will be selected by using the Neuro-Fuzzy Computational Model. The adaptive learning approach used to train the neural network and linguistic labels are allotted to α and γ by associating with the corresponding MAX and MIN threshold values.

4.1. Route Initiation and Discovery Process

Let us depict the MANET as an undirected graph G (V, E), wherein G is a collection of Nodes and E is a collection of neighbours connected by links. (See Figure 3).

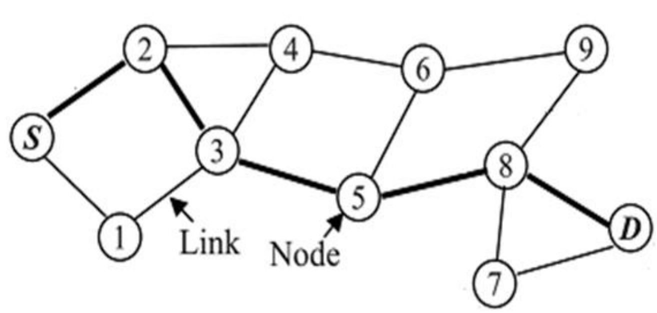

Figure 3 Network Graph G (V, E)

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The Data Packets are sent to the Destination node D from the Source node S. As a result, the Source node S initiates the Route discovery process because, at this early stage, the Source node S lacks routing information about the node D. S emits an RREQ packet with a sequence number and broadcasts it to one-hop neighbours identified through periodic hello request broadcasting. So when RREQ packet reaches at the Physical layer, every node computes the Path Stability Factor(α).

$$\alpha = 1 - \left(\frac{CST}{RSSI}\right)^{\frac{1}{4}} \qquad (1)$$

Where CST is the Carrier Sense Threshold value and RSSI is the Received Signal Strength indicator

RSSI is calculated by each node after receiving packets from neighbor nodes.

$$RSSI = \sqrt{\frac{pt \times \lambda^2}{(4 \times \Pi)^2 \times L \times pr}} \qquad (2)$$

Where Pr is a node's receiving power and Pt is is its transmission power, L is Signal Loss and λ^2 is the signal's wavelength.

Each node also calculates the distance between each other based on the Euclidian distance [24] formula. For instance, the distance across node 1 and node 2 will be calculated as

$$d_{ij} = \sqrt{(x1 - x2)^2 (y1 - y2)^2} \qquad (3)$$

Where $(x1, y1)$ *is the coordinate of node* 1 *and* $(x2, y2)$ *is the coordinate of node* 2

Average Stability Factor (α*) will be calculated using equation (1) and (3) the below equation

$$\alpha^* = p1 \times \frac{d}{T} + p2 \times \frac{\alpha}{T} \qquad (4)$$

Where p1 and p2 are the parameters of α and d respectively and T represents the total number of hops in between sender and the receiver in that route.

The Link Expiry Time (γ) will be obtained by subtracting the current time with range limit of the neighbor can expire.

4.2. Neuro-Fuzzy Inference System Modeling

The calculated values α, γ, and d are converted during the fuzzification process to linguistic values (Low, Medium, and High) based on Min and Max Thresholds. These fuzzified inputs are being used to find out the present fuzzy rules and their effectiveness can be tuned by using the Rule Base which contains all the 27 possible values with the three fuzzy input parameters. (See Table 1).

The Output obtained from the fuzzy rule base was used as input for the formation of neurons in the next level. By using the membership functions the neuron values will be calculated as:

$$n_x = \begin{cases} 1 - (2 \times \alpha^*) & \text{if the output is Very Low or Low} \\ 1 - 2 \times \left[\frac{\alpha^* - 1}{2}\right] & \text{if the Output if Medium} \\ 2 \times (\alpha^* - 1) & \text{f the Output is High or Very High} \end{cases}$$

(5)

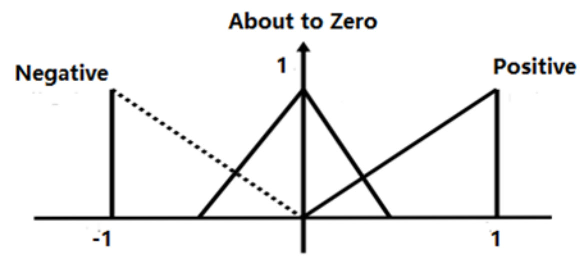

Figure 4 Membership Function

In the next level, the Nueron signal value x_j and y_j is calculated as

$x_j = \frac{j-1}{4}$ and $y_j = 1 - \frac{i-1}{2}$ by choosing i and j as random values between [0,5]

Next, the Sigmoid Neuron Transfer function f is used to calculate the output of the distributed function for both x_j and y_j . All the aggregated input parameters (i_1, i_2, i_3) and the weighted sum was Calculated by using respective weights w_1, w_2, w_3 whose values are in the range [0,1]

$$W = w_1 \times i_1 + w2 \times i_2 + w_3 \times i_3 \qquad (6)$$

The Output of the neuron will be calculated using equation (6) as

$$Output = \frac{Ws}{Sum} \text{ Where } Sum = i_1 + i_2 + i_3 \qquad (7)$$

If the value of the Output is other than Zero-value the Second Layer Neuron will be ready to fire.

The Neuron values are calculated as

$$ns_1 = \frac{1}{1 + e^{i1 \times (sum - i1)}} \qquad (8)$$

$$ns_2 = \frac{1}{1 + e^{i2 \times (sum - i2)}} \qquad (9)$$

$$ns_3 = \frac{1}{1 + e^{i3 \times (sum - i3)}} \qquad (10)$$

In the Third Level, the Calculated values of the Second Level Neurons (equations 8,9, 10) were normalized as

$$nt_1 = \frac{ns_1}{\sum_{i=1}^{3} ns_1} \qquad (11)$$

$$nt_2 = \frac{ns_2}{\sum_{i=1}^{3} ns_i} \qquad (12)$$

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$nt_3 = \frac{ns_3}{\sum_{i=1}^{3} ns_1}$ (13)

Finally, the Neuron value is obtained by multiplying the weighted sum (W_f) with calculation error values (e_1 and e_2) and the output value of the membership function (n_x).

The Calculation error is calculated using

$e_1 = \frac{1}{2*(f_x - n_x)^2)}$ (14)

$e_2 = \frac{1}{2*(f_y - n_x)^2)}$ (15)

$W_f = = \sum_{i=1}^{3} nt_i \text{ x } w_i$ (16)

The final Neuron value (n_f) is calculated using equations 14, 15 and 16 for all the available paths and the path with the highest neuron will be selected by the source node to transmit the data packets.

$n_f = n_x \text{ x } W_f \text{ x } e_1 \text{ x } e_2$ (17)

4.3. Algorithm: ANFIS-ODFTR

Input: Received Signal Strength Indicator (RSSI), Link Expiry Time (γ), Path Stability Factor (α), Average Distance (d)

Output: A Stable Fault Tolerant route

Step 1: For each neighbor node

Step 1.1: Convert the crispy input parameters (γ,α,d) into fuzzy values and assign linguistic labels {VERY LOW, LOW, MEDIUM, HIGH, VERY HIGH} based on Min and Max Thresholds

Step 1.2:Compare all the three calculated input Linguistic parameters using Fuzzy rule base to obtain neuron input parameter

Step 1.3: Calculate the neuron value using the Membership function given in equation (5)

Step 1.4:Calculate the neuron signal values x_j and y_j

Step 1.5:Calculate the output of distribution function using Sigmoid neuron transfer function (*f*) and obtain the weighted sum $W_s = w_1 \text{ x } i_1 + w2 \text{ x } i_2 + w_3 \text{ x } i_3$ where i_1, i_2, i_3 are membership degrees of *f and* w_1, w_2, w_3 are weights whose values are in the range [0,1]

Step 1.6:Calculate Output value using equation (7)

Step 1.7:if output!=0 or output<0 then

Step 1.7.1: Calculate the second level neuron values (ns_1, ns_2, ns_3) using the equations (8), (9) and (10)

Step 1.7.2: Normalize the calculated values to obtain the third level neuron values (nt_1, nt_2, nt_3) using the equations (11), (12 and (13)

Step 1.7.3: Calculate the final neuron value using the equation (17)

Step 2: Choose the Route with Highest neuron value to forward the packets

Algorithm 1 ANFIS-ODFTR

Algorithm of ANFIS-ODFTR is shown in the algorithm 1.

5. PERFORMANCE ANALYSIS THROUGH SIMULATION

The proposed protocol was implemented and simulated in the NS-2 event-driven simulator by varying parameters such as the network size, node speed, and data rate. The proposed protocol's performance was assessed by examining it to the conventional on-demand AODV protocol by Packet Delivery Ratio, Residual Energy Consumption, and Control Overhead.

5.1. Simulation Parameters

Table 2 lists the Simulation setup for evaluating the performance of the proposed protocol.

Parameter	**Value**
Simulator	NS-2.35
Simulation Time	200 Seconds
Simulation Area	1000 X 1000
Transmission Range	250 METERS
MAC Type	802.11
Mobility Model	Random Way Point
Routing Protocols	ANFIS-ODFTR, AODV
Traffic Type	Constant Bit Ratio (CBR)
Initial Energy	100 Joules
Transmission Power	0.02Mw
Receiving Power	0.01Mw
Antenna Type	Omni Directional
Data Payload	1024 Bytes
Network Payload	8 Packets/Second
Number of Nodes	50,100,150,200,250
Pause Time	5 seconds
Data Rate	0.4, 0.5, 0.6, 0.7, 0.8
Speed	1 M/Sec to 5 M/Sec

Table 2 Simulation Setup

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5.2. Performance Metrics

The simulation's purpose is to analyze the performance of the ANFIS-ODFTR protocol, and the following Quantitative metrics are taken on for the performance evaluation:

Packet Delivery Ratio (PDR): The proportion of data packets transported to the destination node to those produced by that of the source node, calculated by

$$PDR = \frac{\text{Total No.of Received Data Packets}}{\text{Total No.of Data Packets Sent}} \text{ x } 100$$

Average Energy Consumption: The ratio of total Initial Energy of All Nodes and Energy Consumed during Transmission of Packets.

Control Overhead: Total Bytes Sent in the Route Discovery Process by Routing Packets.

Residual Energy: The Remaining Energy of the nodes at the closing of the test simulation.

Throughput: The overall data packets (in Bytes) received successfully during in the simulation.

5.3. Simulation Results

Scenario 1: First, simulations are run with a variable nodes count ranging from 50 to 250, with the seed set to 5 M/Sec and the data rate set to 0.4.

5.3.1. Packet Delivery Ratio

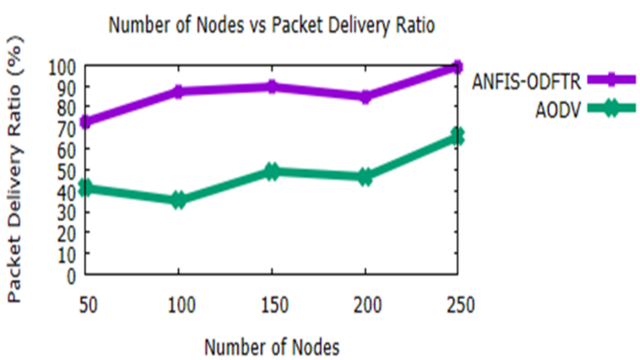

Figure 5 Packet Delivery Ratio against Node Count

It is observed from the simulation results (Figure 5), the proposed protocol shows significant improvement in terms of all the evaluation parameters. The Packed Delivery Ratio was improved more than 35 % than the AODV.

5.3.2. Control Overhead

The ANFIS-ODFTR control overhead is 65% smaller than the AODV (Figure 6). Because the ANFIS-ODFTR maintains stable routes thus the frequent route requests were eliminated particularly in large networks of above 150 nodes.

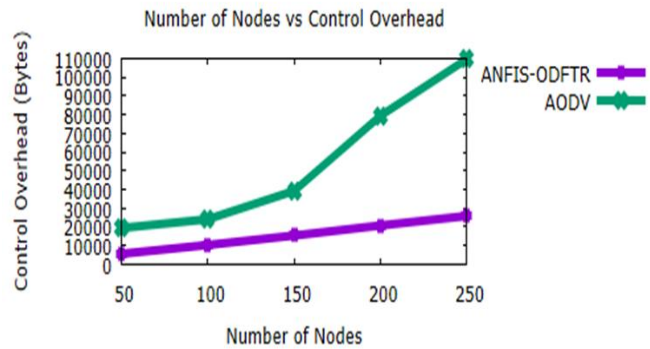

Figure 6 Control Overhead against Node Count

5.3.3. Residual Energy

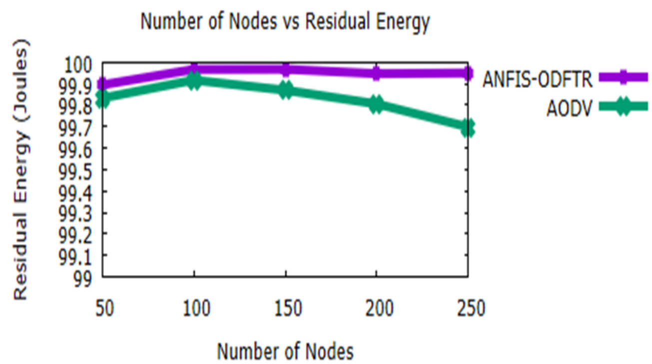

Figure 7 Residual Energy against Node Count

There is nearly 0.15 % positive change in Residual energy also (Figure 7). Every node maintains a threshold of energy and those nodes whose energy falls below the threshold were denying from forwarding the RREQs so that the entire Residual energy of the network shows this positive trend.

5.3.4. Packet Drop Ratio

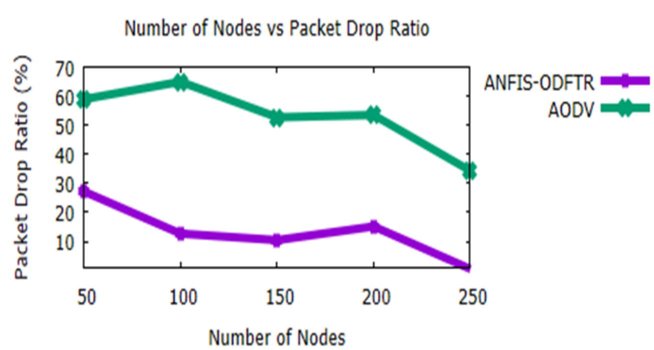

Figure 8 Packet Drop Ratio against Node Count

In the routing table, the proposed protocol keeps track of the routes that are both stable and fault tolerant. The Hybrid computational process eliminates the fault neighbors in the

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neighbor routing table and all the data packets were transmitted through the stable paths only that significantly avoids the packet drops due to frequent link breaks in the network thus the packet drop ratio was reduced drastically (Figure 8).

5.3.5. Throughput

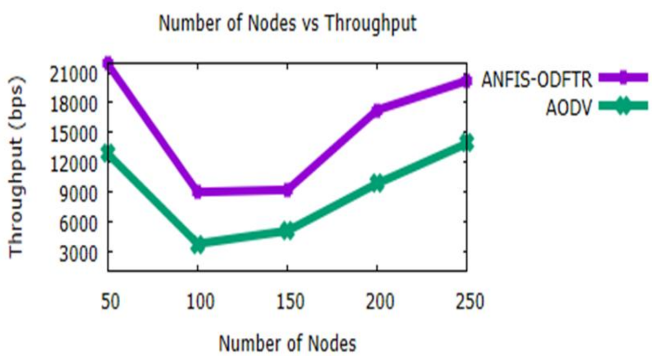

Figure 9 Number of Nodes vs Throughput

The suggested protocol's positive trend in the Packet Delivery Ratio and negative trend in the Packet Drop Ratio demonstrates a considerable improvement in Throughput. There is almost a double-fold increase in Throughput (Figure 9).

Overall the proposed protocol shows a positive trend in all the parameters with the varying number of nodes.

Scenario 2: Later, we ran simulations with the node count set to 50, the data rate set to 0.4, and the speed of the mobile nodes varied from 1 M/Sec to 5 M/Sec for 1 step increase in iterations. The following outcomes were attained after the simulations.

The simulation results (Figures 10, 11, and 12) demonstrated that the proposed approach exhibits substantial improvement in Throughput (Around 19 %), a trustworthy negative trend in packet drop ratio. The Control overhead also reduced drastically, almost showing a straight line.

5.3.6. Control Overhead

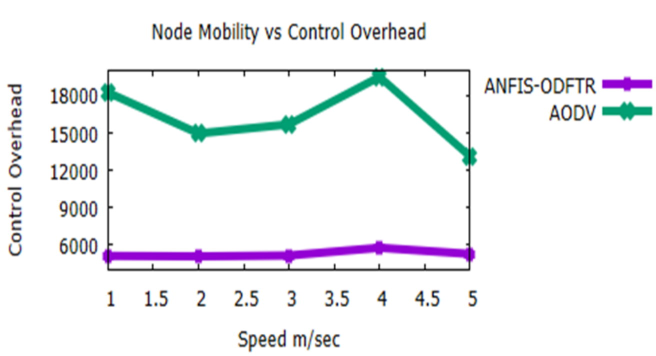

Figure 10 Node Mobility vs Control Overhead

The proposed protocol exhibits less control overhead with varying node mobility. Even with the high mobility of the nodes within the network the control overhead was constant because the proposed protocol keeps track of the future faulty nodes by calculating the stability factor and the reliable routes were maintained thus the fault tolerant rate of the proposed protocol was reliable.

5.3.7. Packet Drop Ratio

While opposed to the conventional AODV, the suggested protocol had a much lower Packet Drop ratio (Figure 11).

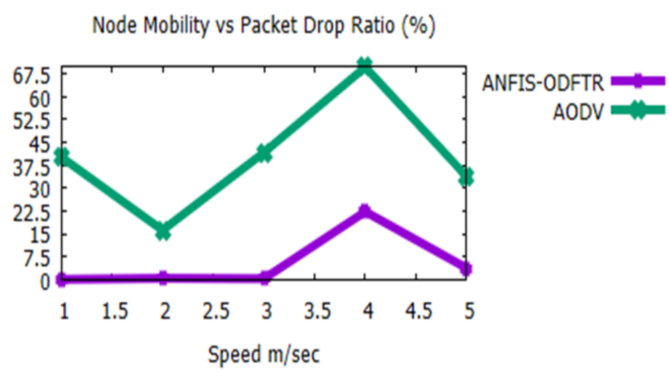

Figure 11 Node Mobility vs Packet Drop Ratio

5.3.8. Throughput

The ANFIS-ODFTR maintains the most consistent routes by calculating the Average path stability factor that reduces the frequent route failures which in turn increases the Throughput.

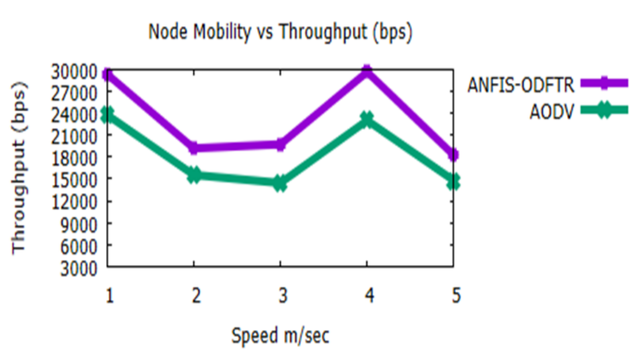

Figure 12 Node Mobility vs Throughput

Scenario 3: In this setup continued the simulations by reserving the node count to 50 and node mobility to and 3 M/Sec and modify the Data Rates between [0.4, 0.8] Mbps.

5.3.9. Control Overhead

For the Small networks of size 50 and, low mobility MANETS, the Control Overhead (Figure 13) is almost constant with all the data rates. This happened because the

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proposed protocol is designed by considering the power constraints and link/route constraints. There is no significance for the variable data rates in the projected protocol.

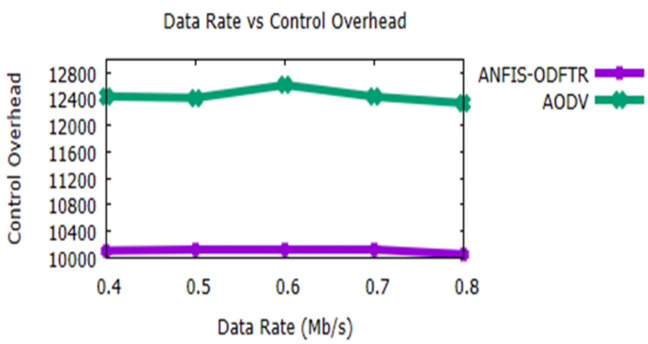

Figure 13 Data Rate vs Control Overhead

5.3.10. Throughput

According to the simulation findings displayed in Figure 14, the suggested protocol maintains Good Throughput even with increased data rates ranging from (0.4Mb/s to 0.8Mb/s).

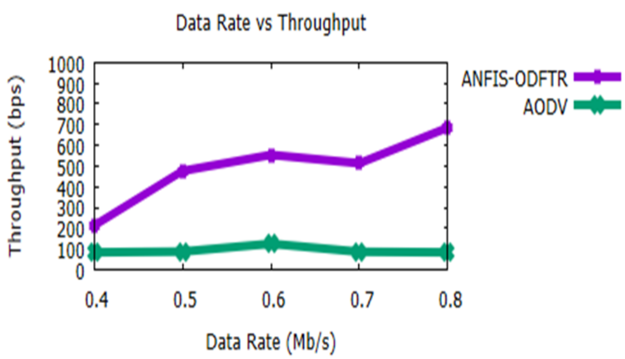

Figure 14 Data Rate vs Throughput

5.3.11. Packet Delivery Ratio

Because of the stable routes, the proposed protocol has a very highest PDR (Figure 15).

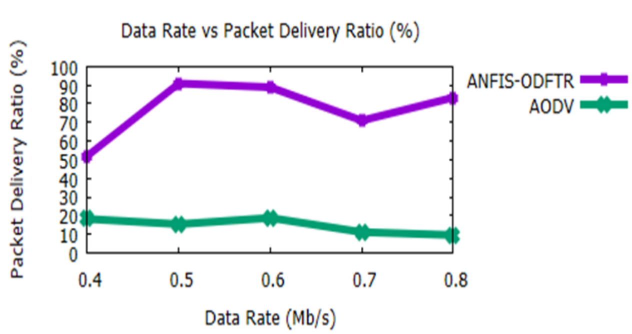

Figure 15 Data Rate vs Packet Delivery Ratio

5.3.12. Energy Consumption

The average rate of consumption of energy of nodes in the network was constant because of isolation of low energy nodes from participation of the routing flow. Data rate vs energy consumption is shown in figure 16.

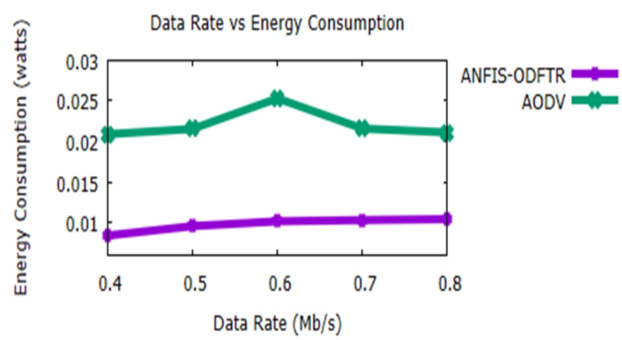

Figure 16 Data Rate vs Energy Consumption

The Scenario 3 simulation outcomes also satisfactorily complimented the performance of ANFIS-ODFTR. The throughput was radically improved whereas the packet drop ratio is almost fall to the lowest. A considerable change was noted in Energy Consumption whereas the control overhead was significantly reduced.

6. CONCLUSION AND FUTURE SCOPE

The Proposed Protocol ANFIS-ODFTR was developed using an Adaptive Neural Fuzzy Inference System in NS-2 and simulations are performed with various parameters. An extensive study with various metrics and compared with AODV protocol gives an overall very good impression that the proposed protocol has proven itself for the fault tolerance in the MANETs. The developed protocol finds their one-hop neighbors by broadcasting the HELLO. Based on the Calculated RSSI value only the neighbors that have the strong signal strength will be added to the neighbors' list. Link Expiry Time was calculated to obtain a more accurate Path Stability Factor. To extend the network's lifetime, nodes assess residual energy and compare it to the threshold value, and prohibit the forwarding of Route Request packets if it falls below the threshold, preventing lower energy nodes from competing in the route discovery phase. Besides, the proposed algorithm used a hybrid Neuro-Fuzzy Computational model to select the best stable path. As ANFIS-ODFTR discovers a stable fault tolerant route, performance metrics were all over improved when compared with AODV. However, the comprehensive computed nature of the Fuzzy Inference System has a little negative impact on packet end-to-end delay. This can be improved further. In future, we would like to improve this protocol further with the assistance of advanced machine learning algorithms.

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REFERENCES

[1] Sheng Liu, Yang Yang, Weixing Wang, Research of AODV Routing Protocol for Ad Hoc Networks1, AASRI Procedia, Volume 5,2013, Pages 21-31, ISSN 2212-6716, https://doi.org/10.1016/j.aasri.2013.10.054.

[2] Almazok, S.A., Bilgehan, B. A novel dynamic source routing (DSR) protocol based on minimum execution time scheduling and moth flame optimization (MET-MFO). J Wireless Com Network 2020, 219 (2020). https://doi.org/10.1186/s13638-020-01802-5

[3] Hussain, Salim. (2011). Effect of Mobility Model on the Performance of DSDV Protocol in MANET.

[4] Thakrar, Payal and Singh, Vijander and Kotecha, Ketan, Study of Routing Limitation of OLSR Protocol in Mobile Ad Hoc Networks (October 18, 2019). Proceedings of International Conference on Advancements in Computing & Management (ICACM) 2019

[5] Y. Chapre, P. Mohapatra, S. Jha and A. Seneviratne, "Received signal strength indicator and its analysis in a typical WLAN system (short paper)," 38th Annual IEEE Conference on Local Computer Networks, 2013, pp. 304-307, doi: 10.1109/LCN.2013.6761255.

[6] Çaydaş, Ulaş & Hasçalık, Ahmet & Ekici, Sami. (2009). An adaptive neuro-fuzzy inference system (ANFIS) model for wire-EDM. Expert Systems with Applications. 36. 6135-6139. 10.1016/j.eswa.2008.07.019.

[7] A. Sarfaraz Ahmed, T. Senthil Kumaran, S. Syed Abdul Syed, S. Subburam, Cross-Layer Design Approach for Power Control in Mobile Ad Hoc Networks, Egyptian Informatics Journal,Volume 16, Issue 1,2015,Pages 1-7,ISSN 1110-8665,https://doi.org/10.1016/j.eij.2014.11.001.

[8] H. Zhong and T. Zhou, "Research and Implementation of AOMDV Multipath Routing Protocol," 2018 Chinese Automation Congress (CAC), 2018, pp. 611-616, doi: 10.1109/CAC.2018.8623785.

[9] Nisha Chaudhary, Er Shiv Kumar Goel, Nitin Goel (2015). A Deep Analysis: Highly Robust Fault Tolerant Secure Optimized Energy Ad-hoc Networks Methodologies for Mobile Nodes. International Journal of Advanced Research in Computer Science and Software Engineering, 5(7), pp.540-543

[10] Ravichandra and Chandrasekar Reddy (2016). Fault tolerant QoS Routing Protocol for MANETs. IEEE International Conference on Advanced Computing, pp.34-45.

[11] Senthilnathan Palaniappan and Kalaiarasan Chellan (2015). Energy-efficient stable routing using QoS monitoring agents in MANET. EURASIP Journal on Wireless Communications and Networking, 13(1), pp.1-11.

[12] Fatemeh Tavakoli, Meisam Kamarei, Gholam Reza Asgari (2016). An Efficient Fault-Tolerance Routing Algorithm for Mobile Ad-hoc Networks. Journal of Advances in Computer Research, 7(2), pp.23-40.

[13] M.S. Gaur, Swati Todi, Vijay Rao, Meenakshi Tripathi, Riti Kushwaha (2017). Multi-constraints Link Stable Multicast Routing Protocol in MANETs, Ad Hoc Networks, DOI: 10.1016/j.adhoc.2017.05.007.

[14] Gopal Singh, Deepak Saini, Rahul Rishi, Harish Rohil, "Role of Link expiration time to make reliable link between the nodes in MANETs: A Review "International Journal of Applied Engineering Research ISSN 0973- 4562 Volume 11, Number 7 2016.

[15] K. Sakthidasan Sankaran, N. Vasudevan, K. R. Devabalaji, T. S. Babu, H. H. Alhelou and T. Yuvaraj, "A Recurrent Reward Based Learning Technique for Secure Neighbor Selection in Mobile AD-HOC Networks," in IEEE Access, doi: 10.1109/ACCESS.2021.3055422.

[16] Xin Ming Zhang, Member, IEEE, En Bo Wang, Jing Jing Xia, and Dan Keun Sung, Senior Member, IEEE, "An Estimated Distance-Based Routing Protocol for Mobile Ad hoc Networks " IEEE Transactions on Vehicular Technology, VOL. 60, NO. 7, SEPTEMBER 2011.

[17] B. H. Khudayer, M. Anbar, S. M. Hanshi and T. Wan, "Efficient Route Discovery and Link Failure Detection Mechanisms for Source Routing Protocol in Mobile Ad-Hoc Networks," in IEEE Access, vol. 8, pp. 24019- 24032, 2020, doi: 10.1109/ACCESS.2020.2970279.

[18] A. Bhardwaj and H. El-Ocla, "Multipath Routing Protocol Using Genetic Algorithm in Mobile Ad Hoc Networks," in IEEE Access, vol. 8, pp. 177534-177548, 2020, doi: 10.1109/ACCESS.2020.3027043.

[19] Sudip Misra et al., "A learning automata-based fault tolerant routing algorithm for mobile ad hoc networks", Journal of Super compt(2012) 62:4–23

[20] J.S.R. Jang, and C.T. Sun, "Neuro-Fuzzy Modeling and Control," Proc. IEEE, vol. 83, no. 3, pp. 378-406, Mar. 1995.

[21] A. Al-Hmouz, Jun Shen, R. Al-Hmouz and Jun Yan, "Modeling and Simulation of an Adaptive Neuro-Fuzzy Inference System (ANFIS) for Mobile Learning" in IEEE Transactions on Learning Technologies, vol. 5, no. 03, pp. 226-237, 2012.

[22] Arkhipov, M.; Krueger, E.; Kurtener, D. Evaluation of ecological conditions using bioindicators: Application of fuzzy modeling. In Proceedings of the International Conference on Computational Science and Its Applications, Perugia, Italy, 30 June–3 July 2008.

[23] E. M. Dogo, O. J. Afolabi, N. I. Nwulu, B. Twala and C. O. Aigbavboa, "A Comparative Analysis of Gradient Descent-Based Optimization Algorithms on Convolution Neural Networks," 2018 International Conference on Computational Techniques, Electronics and Mechanical Systems (CTEMS), 2018, pp. 92-99, doi: 10.1109/CTEMS.2018.8769211.

[24] Osama Younes, Nigel Thomas, Analysis of the Expected Number of Hops in Mobile Ad Hoc Networks with Random Waypoint Mobility, Electronic Notes in Theoretical Computer Science, Volume 275, 2011, Pages 143-158, ISSN 1571-0661, https://doi.org/ 10. 1016 /j.entcs . 2011.09.010.

[25] Singh, K., & Gupta, R. (2021). SO-AODV: A Secure and Optimized Ad-Hoc On-Demand Distance Vector Routing Protocol Over AODV With Quality Assurance Metrics for Disaster Response Applications. Journal of Information Technology Research (JITR), 14(3), 87-103. http://doi.org/10.4018/JITR.2021070106

Authors

Suneel Kumar Duvvuri graduated from Andhra University in MCA during 2012. He is currently working as Assistant Professor in Computer Science at Government College (Autonomous), Rajahmundry. His research interests include Data Structures, Mobile adhoc networks, vehicular adhoc networks, the Internet of Things, Artificial Intelligence, and Machine learning. Presently he is holding the position of Head of the Department of Computer Science at Government College (Autonomous), Rajahmundry.

Dr. S Ramakrishna received Ph.D. in mathematics in 1988. He is professor of Computer science, Sri Venkateswara University, Tirupati. His research interests include Fluid Dynamics, Network Security, and Data Mining. He has guided 20 Ph.D., students till date. To his credit, he has published around 105 research articles in journals of international repute. Presently he is holding the position of Head of the Department of Computer Science at SV University.

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