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An Energy Efficient Routing Protocol and Cross Layer Based Congestion Detection Using Hybrid Genetic Fuzzy Neural Network (HGFNN) Model for MANET

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ABSTRACT

Rapid advancements in wireless communication technologies have resulted in amazing development in adhoc networking. Mobile Adhoc Network has become an essential one in every aspects of our life due to the recent growth of technological developments. Effective communication in right scenarios is an important factor to be considered. Mobile adhoc networks, is a subclass of adhoc networks, nearly have similar features as adhoc networks, offering many obstacles in designing a path for transmitting information from source to destination. As a result, the network may be susceptible to suspicious network events as a result of factors such as connection errors, buffer overflows, layers, and so on. In this research, the Hybrid Genetic Fuzzy Neural Network (HGFNN) method is employed for a cross-layer based congestion detection and energy efficient routing protocol. When a network event happens in this protocol, the kind of event happening is detected to handle it properly. Following that, other data transmission pathways are established by using the idea of hybrid approaches to some of the essential parameters. Suitable routes are established and data messages are effectively conveyed based on the learning processes used in this study by employing a hybrid genetic fuzzy neural network method that ensures adaptive and rapid data communication. The suggested technique aims to reduce energy utilization, transmission delay, enhance packet delivery ratio, hence increasing throughput. Suggested method's efficiency is calculated by assessing its performance in network simulator with respect to energy utilization, transmission delay, and packet delivery ratio.

Index Terms — Wireless Communication Technology, Hybrid Genetic Fuzzy Neural Network (HGFNN), Mobile ad hoc Networks, Congestion detection, Routing.

I. INTRODUCTION

Because of the node mobility, there is no predetermined infrastructure in Mobile Adhoc Networks (MANETS) [1]-[2]. Because this is a volatile environment, nodes can enter and exit the network at any time without participating in data transfer, making route building difficult [3]. To ease communication, all nodes must collaborate, that needs every node to become highly smart as it can perform not just as a network host for broadcasting and obtaining information, and also as a network router for packet forwarding from other nodes.

Congestion control and power control across all levels are significant issues for MANETs. To overcome these challenges, the multiple levels of protocol stack intercommunicate with each other in the suggested cross-layered solution. Congestion results in drawbacks like long delays, expensive overhead, and a higher number of packet losses.

Imagine an n-node Adhoc network; a link is formed among source S and destination D such that information may be exchanged through in-between nodes. After numerous senders strive for link bandwidth in a common network, data rate must be regulated to prevent network overload. If a packet cannot be forwarded by the router, it is dropped, resulting in packet loss. The lost packet might have passed through numerous intermediate nodes, consuming substantial network resources like bandwidth, energy, and so on. The lost packet causes rebroadcasting, increasing network traffic. As a result, congestion of network has a significant impact on network throughput.

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Congestion management techniques in MANET are presented in the same way that they are in any other network; whereas when packet number transferred exceeds the predetermined network capacity, this will end in loss of packet, reduced throughput, increased delay since network resources are limited. Congestion will occur in the network as traffic increases, requiring more bandwidth. In these networks, packets are exposed to interference, and because of the use of a shared wireless channel and the existence of an ever-changing topology, packets could fade. All the broadcasting mistakes contribute to network overload [4]-[5]. Because the nodes are movable and the shared channel is unreliable, data transmission is delayed and data packets are lost. The delay in this scenario is because the change in path taken to attain destination and should not be misunderstood as a result of congestion. When there is a change in route, packets may be lost. As a consequence, this should not be misinterpreted as a congestion issue, as this might lead to incorrect responses when employing the congestion control approach. Furthermore, it is hard to keep track of packet lost numbers since, as transmission time varies, so does round-trip time and degree of competition for access to the medium [6]. A congestion detection technique must be used to evaluate the link layer occupancy at all times to identify possibility of congestion at an early stage. To do this, the node must be at a position that guarantees low delay and high throughput while maintaining an satisfactory queue size [7]. when an appropriate congestion control method is not used, there might be congestion collapse, resulting in data loss. For avoiding congestion and connection difficulties, effective congestion control strategies must be implemented [8].

Cross-layer design is used in the sharing of node status information as well as the management of its actions to control network performance among stack layers by combining the three layers, physical, media access control, and routing layers, to avoid congestion at advanced layer, application layer [9]. In cross layer-based congestion control strategy, communication occurs between MAC and physical layer to gather node status data and derive connection quality. Whenever node signal condition is verified to be satisfactory, subsequent stage is to identify the interference and contention which may exist at nodes; when the 2 elements are found to be excessive, the network become congested. As a result, the MAC layer sends data to application layer to notify it of the possibility of congestion, application layer slows transmission rate. routing layers select data broadcasting channels based on the information supplied by physical and MAC layers. Congestion control is achieved at transport layer depending on redundant information of routing layer received from data information collected at routing layer [10]- [11].

In the prior work [12], they introduced a multiobjective cross-layer based multipath routing system. The paths for data packet transmission in this protocol are chosen by hybrid routing. In addition, a cross-layer measure depending on Expected Transmission Time (ETT), Residual Energy, Load-Balancing Factor has been developed. This cross-layer measure is used in conjunction with hybrid routing protocol to determine the best path depending on cross-layer measure. Here, we suggest to construct a cross-layer based congestion detection system that triggers cross-layer based multipath routing for optimal routes as an addition to this work. As a result, employing the Hybrid Genetic Fuzzy Neural Network (HGFNN) method, a cross-layer based congestion detection and energy efficient routing protocol is suggested in the study.

II. Literature Survey

Minimum Battery Cost Routing (MBCR) was suggested by Singh et al. [13]. The MBCR routing protocol computes the total of all nodes in a path's residual power, that is employed to determine optimal route among source and destination. However, the technique does not take into account individual node residual power and may choose a route with mobile nodes with low power. suggested approach ensures network energy fairness.

Suri et al. [14] suggested "QEPAR," a bandwidth-efficient power-aware routing system. The routing protocol deals with issues of delay and bandwidth. QEPAR improves performance by reducing packet loss caused by a node not having adequate battery power to rebroadcast the data packet to next node. The suggested approach is also useful in determining an optimum path that does not contain any loops.

Kumaran et al. [15] presented EDAODV as another congestion control technique for regulating congestion in AODV, that identifies congestion at node. It computes the queue status value and hence determines congestion state. Furthermore, non-congested predecessor and successor nodes of a congested node are employed by it to initiate a bi-directional route-finding procedure to establish a substitute non-congested route among them for data transmission. It searches for numerous alternative pathways before selecting the optimal path for data transmission.

Congestion and Energy Aware Routing Strategy was suggested by Nedumaran and Jeyalakshmi [16] as a combined energy and congestion measure based routing protocol (CAERP). It is built on DSR and controls congestion by varying the data rates of nodes. The protocol employs cross-layer information, the Received Signal Strength Indicator (RSSI), node queue size to estimate distance and congestion. Nodes with a large queue size that are congested are exempted from data rate changes. The data rate for other nodes varies depending on the queue size and RSSI value. The findings show a reduction in congestion, increased energy consumption, and an increase in throughput.

Terdal et al. [17] suggested ELB-MRP that incorporates a mixed traffic integrated energy cost to improve the routing strategy by including disturbance created by the neighbour impact to routing decisions while conserving energy.
The contention window and queue size are utilized to calculate the load on a node and its nearest one-hop neighbours. Energy is considered while deciding on a route. The simulated results indicate that the suggested strategy improved performance.

The major purposes of the MAC layer and network layer in a [18] wireless sensor network are to identify collisions, distribute channel resources, choose pathways, and send data, etc. To reduce network congestion and preserve network energy, a cross-layer optimization strategy depending on the power control is presented.

It seeks to resolve challenges among protocol levels in wireless sensor networks such as relative independence, lack of information exchange, inability to meet network demands on time, inconsistency among network node transmission power and network energy, etc. The simulation findings demonstrate that, when compared to other methods, the PCSC method improves network performance, saves network energy, and extends network lifespan.

Tabash et al. [19] proposed a technique known as fuzzy logic TCP that employs a fuzzy logic-based inference system on aspects like predicted and actual throughput. Size of the congestion window is determined by these characteristics. The findings indicate that this technique improves TCP performance by not relying on peripheral feedback such as modifications done by sender-based on specific factors. Nevertheless, this method takes longer to process.

Douga and Bourenane [20] established a hybrid TCP approach which is created by increasing IEEE 802.11 standard and TCP-Reno protocol and developing a cross-layer design by allowing TCP to distinguish causes of packet loss like congestion, network problems, etc. The signal strength is an essential factor in calculating the node position. Depending on this, round-trip time of information message is computed and compared to the true RTT to ascertain cause of packet loss, and subsequent phase is done appropriately. The findings indicate that this strategy lowers packet loss and congestion while also resolving network issues. Unfortunately, QoS measurements are not taken into account.

Rath et al. [21] proposed a MSG formed on cross-layer congestion management approach. Here, transmission power and TCP flow rate are sustained at a suitable level by increasing JOCP without information transfer, such that there is no monotonic connection among state variables under study. Non-monotonic relationships are assessed through dividing them into monotonic relationships. A sequential optimization technique is then applied. In this case, all control variables are continually updated one after other until goal or control variable assignment remains unaffected. Nevertheless, when compared to the other method, performance is lower.

III. Proposed Methodology

This protocol detects and identifies concurrent instances of network events [22]. The connection is stated to be in risk of being destroyed whenever the signal strength of a packet received falls below a specific level. Whenever a receiver obtains a damaged packet as a consequence of a CRC error, it's doesn't send an ACK packet in response. When the retransmission timer expires, transmitter does local forwarding at link level till transmission is successful or it approaches relevant retry threshold. When retry point is reached, it means that packet was lost because of channel issue. Instead, a node on route to destination indicates that buffer size has exceeded a predetermined limit. After concurrently identifying and distinguishing congestion level, the Hybrid Genetic Fuzzy Neural Network (HGFNN) method [23] is used to determine the ideal route based on the detected and combined congestion status. As input variables, Hybrid Genetic Fuzzy Neural

Network (HGFNN) method considers network interruptions, channel error, link layer contentions. The combined congestion state is assessed based on the output, and optimal routes are chosen to enable adaptive and rapid data transfer (Figure 1).

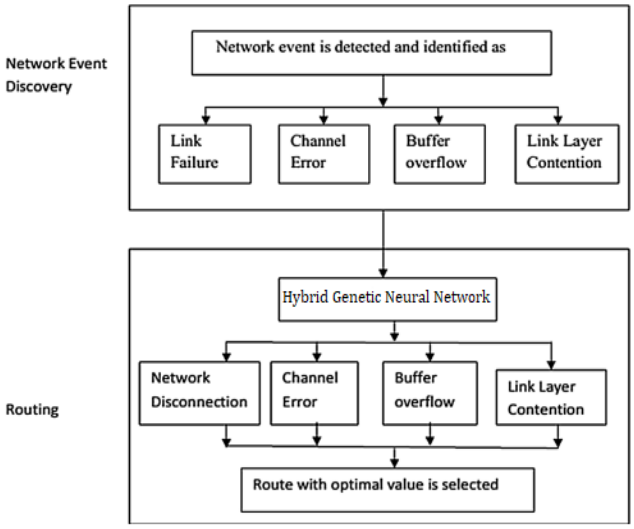

FIGURE 1: PROPOSED BLOCK DIAGRAM

3.1. Network Event Recognition and Identification

A. Recognition and Identification of Network Events

Algorithm 1 depicts recognition and identification of network events.

Events Recognition and Identification

1. S originally transmit data message towards D via arbitrarily chosen several paths.
2. Assess signal power difference

$D_{m,m-1} = S_m - S_{m-1}$ (1)

here S Source node, D Destination node,

3. If $D_{m,m-1} > 0$ then

   S and D are approaching each other.

   Else if $D_{m,m-1} < 0$, then

   S and D are traveling away from each other.

   End if

4. Estimate $E_{m,m-1}$ as
   $E_{m,m-1} = \alpha \times D_{m,m-1} + (1-\propto) \propto\times D_{m-1,m-2} + \cdots + (1-\propto)^n \propto\times D_{m-n,m-n-p} + \cdots + (1-\propto)^{q+1} d_{0,1}$
   (2)
5. $If\, S_m < threshold, and\; E_{m,m-1} < 0$, then
   Error is identified as link failure
   End if
6. If S transmit message, then
   6.1 While RTN not expired

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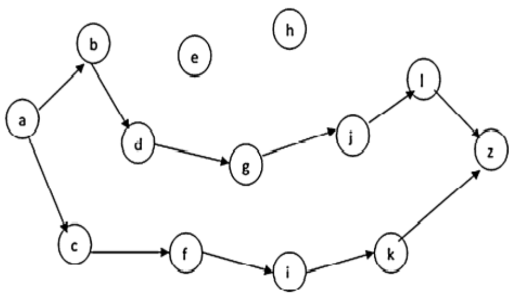
6.1.1 If ACK is received, then
Break
Else
Wait
End if
End while
End if
7. If ACK is not received, then
7.1 While RT_{limit} not reached
S rebroadcasts information
End while
End if
8. If ACK is not received, then

Error is identified as a channel error

End if

9. If $BufSize_i > BufTh$ at N_i, then
N_i sets ECN flag for packets in buffer
End if
10. If D receives ECN flag in data packet
D sets ECN flag in ACK packet
Error is identified as buffer overflow
End if
11. If $LLcnt > LLcntTh$, then
Increase $LLrcnt$
End if
12. If $LLrcnt_{limit}$ is reached then
Packets dropped
NtMess send to S
End if
13. If S receives NtMess, then
S retransmits the data
Error is identified as link layer contention
End if

The source employs a window-based exponential averaging approach while transmitting data message to alleviate the impacts of channel disappearing and unpredictable transient interventions (Figure 2)



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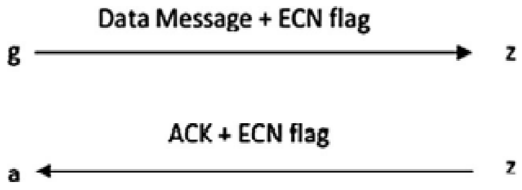

FIGURE 2: NETWORK WITH SOURCE NODE, TRANSMITTING MESSAGE TO DESTINATION NODE, Z VIA INTERMEDIATE NODES B, D, F, G, J, AND L [24]

While an interim node detects that buffer capacity exceeds a predetermined threshold, it uses a probability function to set the Explicit Congestion Notification (ECN) flag of packets in its buffer. Whereas if ECN flag is set in a data packet, destination should set it in return ACK packet to alert source of buffer overflow occurrence.

A link-layer retry amount is preserved to assess link-layer contention level when backlogged queue at a node because of link layer congestion reaches a predefined threshold during data transmission. While average retry amount exceeds a specific threshold, packets begin to be lost, a warning message advising source node of the packet loss is sent. data packet is subsequently resent by the source. The cause of this problem is link layer contention.

3.2. Routing using Hybrid Genetic Fuzzy Neural Network (HGFNN) Method

HGFNN method is used in routing process. When source doesn't obtain acknowledgement data, it retransmits data message to destination when the retransmission timeout expires, using a new optimum route formed on HGNN.

Because of their computing efficiency and easy formulations, triangulation functions are often employed in real-time applications. Network disconnections, channel error, link layer contentions are evaluated as input factors for selecting ideal route based on the observed and aggregated congestion state. The combined congestion condition is assessed based on the output, and the best paths are chosen.

1. Disconnections of Network are regarded as a significant factor for determining best path. Since likelihood of disconnections of network increases along the path, likelihood of an ideal path decreases, that is., disconnections of network and best path are inversely proportional to each other.
2. Another key consideration in determining the best path to the destination is channel error. As channel errors rise, the path becomes highly prone to failure, so channel error and optimal path possibilities are inversely related.
3. Buffer overflow is also a critical deciding element in determining the best course to take. If the buffer overflows, the route's probabilities of remaining optimum decrease. As a result, buffer overflow and best route possibilities are inversely proportional.
4. Link layer contention is subsequent critical deciding element in determining the best path to choose. As link layer contention grows, likelihood of path being optimum decreases. As a consequence, link layer contention and best route possibilities are inversely related.
5. The ideal path is determined based on the hidden layer weight value of 3 input criteria: network disconnection, channel error, buffer overflow, link layer connection.

3.2.1. Genetic Algorithm (GA)

GAs are adaptive heuristic search techniques which are a subset of evolutionary algorithms. Natural selection and genetics are the foundations of genetic algorithms. These are intelligent applications of random search aided by previous data to guide the search into the area of higher performance in the optimal solution. They are widely used to provide high-quality optimal solutions and search issues. Natural selection is simulated by genetic a algorithm, that implies that species that can adjust to environmental changes will be capable of live, reproduce, pass on the subsequent generation. Conversely, they replicate "survival of the fittest" amongst individuals of successive generations in order to solve a problem. Every generation is made up of individual population, with every individual representing a point in the search space and a potential result. Every individual is chosen entirely by a string of characters, integers, floats, and bits. The string is comparable to Chromosome.

The GAs maintains track of an n-individual population (chromosomes/solutions) and its fitness ratings. Individuals with greater fitness ratings are more likely to reproduce than others. Individuals with better fitness ratings are selected to mate and produce healthier offspring by combining their parents' chromosomes. Since the population is fixed, place for immigrants must be made. As a consequence, a few individual died and were substituted by newcomers, eventually giving birth to a new generation when the previous population's mating chances were exhausted. It is envisaged that as generations pass, better solutions would develop, while the least suitable will be phased out. Every new generation has high "better genes" than preceding generation's person (solution). As a result, each successive generation has better "partial solutions" than prior generations. The population has converged when offspring formed have no substantial difference from the offspring generated by prior populations. Method is believed to have converged on a set of problem solutions.

Following the creation of the initial generation, the method evolves the generation using subsequent operators.–
1) Selection Operator: objective is to provide priority to individuals with high fitness levels and permit them to pass on their genes to future generations.

2) Crossover Operator: Mating among individuals is represented by this. The selection operator is used to choose two individuals, and the crossover locations are determined at random. The genes at these crossover locations are then transferred, resulting in the creation of a completely new individual (offspring).

3) Mutation Operator: primary concept is to inject arbitrary genes into offspring in order to preserve population variety and prevent early convergence.

The entire algorithm may be summarized as follows: –
1) Randomly establish populations p

2) Calculate population fitness

3) Repeat until convergence:

   a) choose parents from population

   b) Crossover and produce new population

   c) Do mutation on new population

   d) Compute new population’s fitness

3.2.2. Fuzzy Neural Network

A fuzzy NN, also known as a neuro-fuzzy system, is a learning machine which employs NN approximation method to investigate factors of a fuzzy system (fuzzy sets, fuzzy rules). There are several similarities between NNs and fuzzy systems. They are employed to solve issue (for instance, pattern recognition, regression, or density estimation) if no mathematical model of the problem exists. They only have a few drawbacks and benefits that are almost completely eliminated by integrating both ideas. NNs is used when the problem is described by large enough number of observed cases. These observations are sent into black box, which is then trained. On one hand, no previous understanding of issue is required. Conversely, extracting understandable rules from the structure of a neural network is difficult. A fuzzy system, on the other hand, requires language rules rather than acquiring instances as previous knowledge. Moreover, input and output variables must be linguistically defined. When information is insufficient, incorrect, or conflicting, fuzzy system should be modified. Because there is no formal technique, tuning is done on a heuristic basis. It is typically time-consuming and error-prone. Figure 3 shows the structure of fuzzy neural network.

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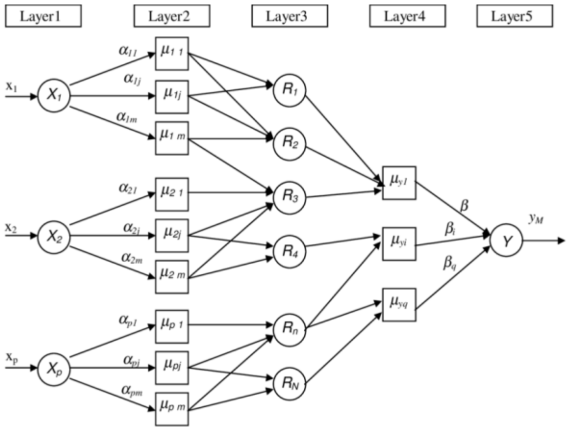

FIGURE 3: STRUCTURE OF FUZZY NEURAL NETWORK

3.2.3. Genetic Fuzzy Neural Network

Topology of HGFNN method that offer is similar to that of the Sugeno controller. The crisp input vector $x_p \in R^{m\times1}$is first fuzzified by vector of membership functions in m separate property dimensions $\hat{f} = (\mu_1, \dots, \mu_m), f: x \to [0, e]$, here e is regarded as them-dimensional unit vector. fuzzy vector $\hat{f}$(x) is then gathered to fuzzy signal by T-norm, i.e. α_p =T ($\hat{f}$(x_p)). When necessary, input features x_j of X are described with respect to membership in every three linguistic property sets: poor, medium, good. As a result, rather than the above-mentioned separate property fuzzy vector, an m-dimensional pattern x=(x_1,…,x_m) is indicated by 3m fuzzifier.

$$\hat{f} = (\mu_{1,poor}, \mu_{1,medium}, \mu_{1,good}, \dots, \mu_{m,good}) \qquad (3)$$

Take L=1 and LMAX be total predetermined runs, T be highest number of repetitions employed in stages 1–4.

Step 0: In fuzzier $(\hat{f})$ and defuzzifier$(\hat{h})$, provide membership functions. Adjustment factors (learning rates for $\hat{f}$ and $\hat{h}$) must be specified. Set the boundaries for $w = \hat{f}^T, \hat{h}^T)^T$ to the values given in [left, right]. Assume t = 0, then define $F(w;\ \rho t)$ in (3) and supply the population.

$$POP(t) = [w_{1t}\ \vdots\ w_{Nt}\ ] = [(x_{1t}, y_{1t})\ \vdots\ (x_{Nt}, y_{Nt})\ ] \qquad (4)$$

Here $w_{it}$is starting (present best) result, $w_{it} \in [left;\ right];\ \forall i.$

Step 1: POP(t) should be evaluated and ranked in increasing order utilizing $F(w;\ \rho t + (L-1)T\ )$ as shown below. Load x_p and use it to categorise the observation (5.12). If ˆgp 6= gp, proceed to step 2, otherwise proceed to step 3.

Step 2: Assume gˆ p and gp be membership functions for false and true fuzzy output groups, respectively. Alter functions' convexity=concavity infinitesimally by learning ratio to make false group less appealing and actual group more appealing. If ˆgp = gp, proceed to step 3; otherwise, infinitesimally change convexity/concavity of critical membership function(s) in fuzzier f, that is., function(s) activating collective signal to mapping vector function h˜, so that ring level of adjusted signal makes true group highly attractive and false group less attractive.

Step 3: Using arithmetic mixed-integer crossover and non-uniform mixed-integer mutation, choose N=2 greatest individuals from POP(t) and produce N new individuals in POP(t + 1).

Step 4: Steps 1–3 must be repeated till convergence, or L = LMAX, is reached. ending condition is defined as: Assume F(t) be moving average of optimal objective function values acquired over a predetermined number of repetitions. Then halt.

Incorporating GAs into fuzzy systems eliminates the problems associated with manually selecting appropriate rules and membership functions for a specific task. The GA is in charge of selecting a high-performing rule set and fine-tuning the membership functions in relation to the rule set. This leads in high-performing, robust routing algorithms that can operate across a large parameter range and are almost entirely computer-designed.

GA is utilised to improve the initial rule-set as well as the routing Unit's membership functions. The ability of the chosen route to meet the desired QoS requirement at a cheap cost and without breaking policy is critical to success. The following QoS parameters have been established for edge nodes: throughput, end-to-end delay, and data loss rate. Routing Unit's fuzzy section assesses the potentiality of each possible route. The Routing algorithm's result will be obtained once all feasible routes have been examined, or when a route is deemed adequate in terms of the evaluation function being larger than a threshold. The following hops that are evaluated are selected from among the neighbouring nodes depending on their performance evaluation.

IV. Experimental Result And Discussion

Table 1. shows the simulation factors. NS-2 version 2.32 is used to assess CCDRT performance. Assume an arbitrary network distributed in a region of 1250 9 1250 m. packet transmitting rate is adjustable between 50, 100, 150, 200, 250 Kb. total flows varies between 2, 4, 6, 8, and 10. As MAC layer protocol for wireless LANs, IEEE 802.11's DCF is employed. CBR traffic with UDP source and sink is simulated.

Table 1: Simulation Factors

total nodes	110
Size of Area	$1250\ 9 \times 1250\ m$
MAC	802.11
Simulation time	50 s
Traffic source	CBR
Packet Size	512
Speed	10 m/s
Rate	50, 100, 150, 200, and 250 Kb
CBR traffic flows	2-10
Propagation model	Two Ray Ground
Antenna type	OmniAntenna

CCDRT-HGNN performance is compared to CCDRT [24] and A-DSR [22] protocols. The following measures are used to assess performance primarily.

Average End-to-End Delay (E2E delay)

E2E delay is calculated by averaging entire surviving data packets from sources to destination.

Average Packet Delivery Ratio

It is proportion of total successfully received packets to entire packets broadcasted.

Drop

It is amount of lost packets while data transfer.

i. Based on Flows

The number of flows in the initial experiment is changed as 2, 4, 6, 8, and 10 with a rate of 50 kb.

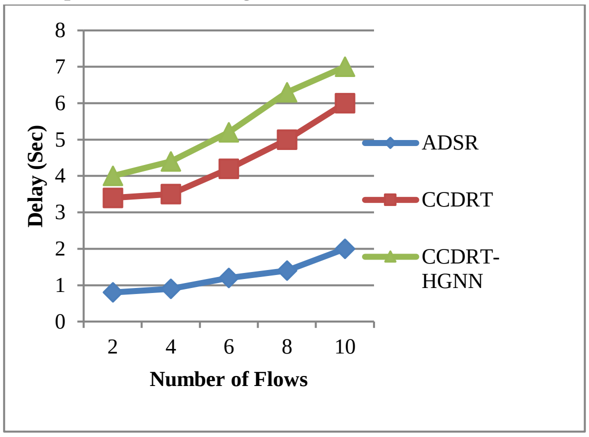

Figure 4: Flows versus delay

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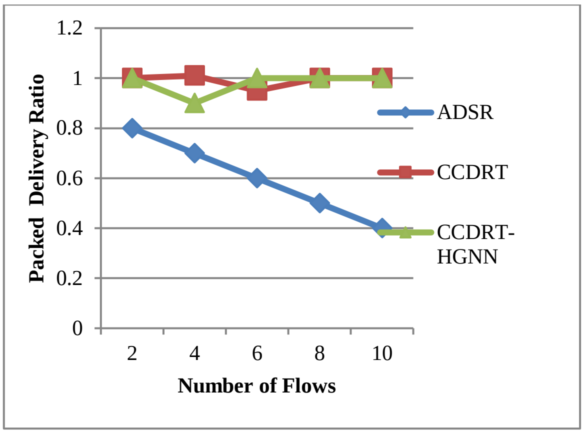

FIGURE 5: FLOWS VERSUS DELIVERY RATIO

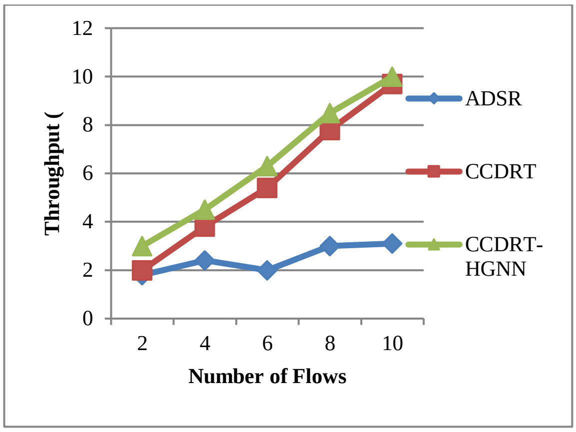

FIGURE. 6: FLOWS VERSUS THROUGHPUT

Figures 4, 5, and 6 depict the delay, delivery ratio, throughput findings for number of flows 2, 4, 6, 8, and 10 in CCDRT, ADSR, as well as suggested CCDRT-HGNN protocols. Whenever the three protocols' performance is compared, we conclude that CCDRT-HGNN exceeds ADSR and CCDRT with respect to delay, delivery ratio, throughput.

ii. Based on Rate

In 2nd experiment, total packets sent per second is adjusted between 50, 100, 150, 200, and 250 kb, with flows ranging from 10 to 100.

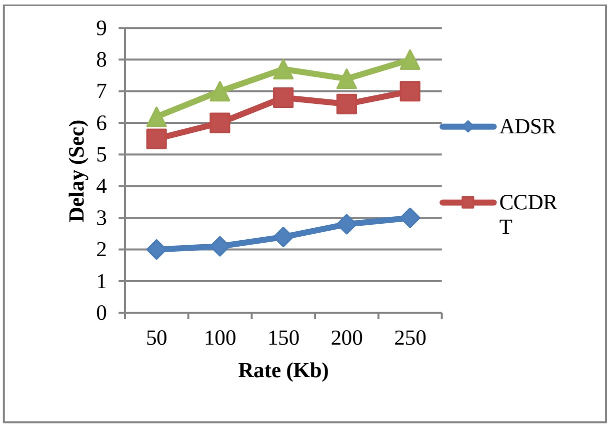

FIGURE. 7: RATE VERSUS DELAY

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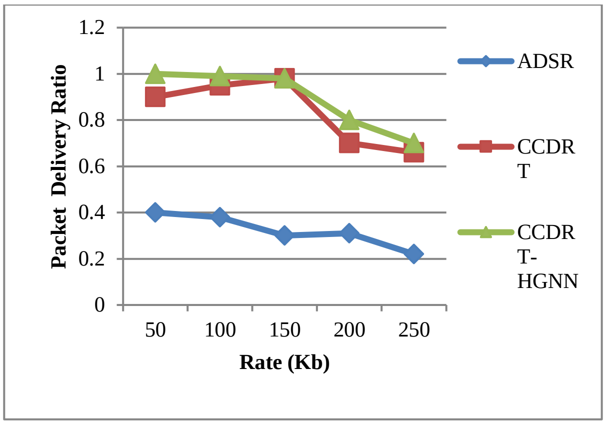

FIGURE. 8: RATE VS DELIVERY RATIO

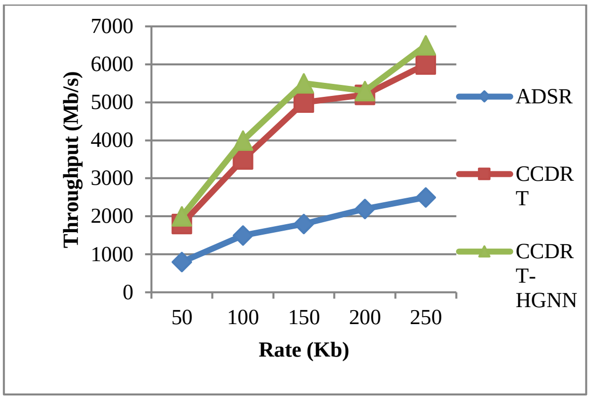

FIGURE. 9: RATE VS THROUGHPUT

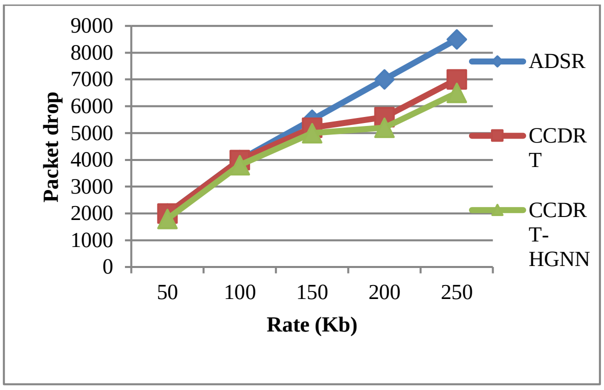

FIGURE10: RATE VS DROP

Figures 7, 8, 9, and 10 depict findings of delay, delivery ratio, drop, throughput for packet sending rates of 50, 100, 150, 200, and 250 kb in the CCDRT-HGNN, CCDRT, ADSR protocols. While performance of three protocols is compared, CCDRT-HGNN exceeds other protocols regarding delay, delivery ratio, throughput, drop by 8%.

V. CONCLUSION

here, abnormal network events that occur while data broadcast are recognized and recognized as one of four probable errors, which include link failure, channel error, buffer overflow, link layer conflict. When fault kind has been determined, data is routed through different pathways. new alternative paths are determined through running the Hybrid Genetic Fuzzy Neural Network (HGFNN) method on 3 parameters: network disconnection, channel error, buffer overflow, link layer conflict. output optimum path is chosen via selecting path with best value, that is generated through concurrently evaluating 3 input parameters as per Neural Network.

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