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Improved Adaptive Neuro Fuzzy Inference System Based Congestion Control for Wireless Network

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Abstract: The multi-hop wireless network has been a crucial addition to wired networks for the goal of ubiquitous networking. Quality of Service (QoS) support in multi-hop wireless networks is a topic of extensive research due to the widespread utilization of multimedia applications that demand QoS guarantees. The initial step in providing QoS assurances in multi-hop wireless networks is typically acquiring information on end-to-end available bandwidth. A wireless Congestion management Scheme based on Extended Kalman filtering and Bandwidth (CSEKB) is created in this earlier study. By constructing a noise perception factor, the CSEKB is able to discern between different types of packet loss and effectively observe the bandwidth oscillation of (WNs). The congestion management parameters are modified in accordance with the congestion factor to enhance the performance of the WNs. The CSEKB, unfortunately, is unable to resolve the issue of congestion collapse brought on by numerous packet collisions in shared media. The machine learning or soft computing methods are needed to deploy in the congestion control. In order to fix this issue, the proposed system designed a Hidden Markov Model with Improved Adaptive Neuro Fuzzy Inference System (HMM -IANFIS) for available bandwidth prediction and congestion detection in wireless network. In wireless network, to predict the available bandwidth rate Hidden Markov Model (HMM) is utilized. Additionally, the prediction outcome serves as the foundation for the subsequent step of congestion detection. Then based on the actual optimal sending rate and smoothed delay, perform congestion detection with the help of IANFIS. The experimental data demonstrates that the suggested system achieves great performance in terms of packet delivery ratio, end to end delay, and throughput when compared to the earlier techniques.

Keywords: *HMM, ANFIS, Wireless Network and congestion control*

1. Overview

The expansion of wireless technology has sparked the advent of applications, protocols, and scenarios that have benefited human endeavours. To serve a variety of applications, services, and transmissions, scalable and dependable communication networks are required [1]. Uncontested advantages of wireless networks necessitate ongoing algorithm and protocol research and refinement to effectively control network functionality and capacity. Sensor networks, machine-to-machine communications, the Internet of Things, millimetre-wave techniques, multiple input multiple output technology, and many more recent advancements have helped to increase the effectiveness of communication and data transmission through wireless networks. In order to maximise the functionality of diverse wireless communication networks, policies and guidelines on bandwidth distribution have been developed [2–3]. Numerous studies have been conducted in the field of determining the bandwidth that is available. The two forms of active bandwidth approximation practices are Probe Gap Model (PGM) and Probe Rate Model (PRM). The primary basis for estimation in PRM is the probe rate between sender and receiver [4].

Congestion, which affects all types of communication networks, is one of the main subjects with wireless networks (WNs). The WN's era is shortened by congestion, which also results in packet loss. Finding and identifying congestion in a wireless network is referred to as congestion detection [5]. When a node or connection is delivering more data than it can manage, congestion results, lowering the network's quality of service. The network's congestion causes packets to drop, lengthens the processing time for them, and lowers throughput. Congestion cannot be predicted using just one parameter value. For identifying network congestion, factors including network topology, application, and bandwidth utilisation are taken into account. As techniques for detecting congestion, recent works use the channel's condition, the queue's length, the service period of the packet, the interval between packets, the packets' drop rates at BSs, and the queue's length. A new method of detecting network congestion is required, one that reduces the computational complexity and battery life utilization of the sensor node. Congestion detection is the procedure of identifying, locating, and analysing the presence and position of congestion in WSNs [6]. When the QoS of a

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network deteriorates, it may lead to packet loss, queuing delays, or a growth or diminution in the throughput of the network. Often, one measure cannot reliably identify congestion.

Wireless network congestion control relies heavily on accurate and effective congestion detection. The majority of algorithms were built using some congestion control measurements to gauge how well their protocols were being executed. Congestion Detection and Avoidance (CODA) is presented in [7]. For accurate, low-cost inference of congestion at each receiver, CODA combines the current and historical settings with the present buffer possession. However, the reliability is diminished. When an equal number of packages are doing receive out of apiece node to the BS or descend by means of preserving a distinct queue with each their former hop node, fairness is achieved according to the Congestion Control and Fairness (CCF) scheme introduced in [8], that does not only eradicates overcrowding but also ensures fair distribution of packets to the BS. Based on packet service time, CCF can identify congestion and manage it in a hope-by-hope fashion. However, CCF does not detect underutilized nodes or links because it solely measures packet service time to spot overcrowding.

The rest of this paper is prearranged as trails. Section 2 familiarizes the overview of previous introduced available bandwidth prediction and congestion control methods. Section 3 describes a HMM -IANFIS approach. Section 4 describes the researches and analysis outcomes. Finally, conclusion of the work is provided in Section 5.

2. Literature Review

At the transmitter end, Tang et al. (2022) introduced TCP-WBQ, a variation of TCP that promptly responds to actual overcrowding and effectively protects against arbitrary packet loss. The newly developed congestion control technique first ideas a back-log system is constructed by received request from multiple intended services and service request from the user. Congestion control and packet delivery factors also considered for performance evaluation. TCP-WBQ maintains a trade-off amongst high throughputs and congestion avoidance by more correctly detecting congestion degrees and implementing the related strategies of changing the congestion window [9].

A customizable packet flow ratio and reduced endwise delay are achieved with the help of Malarvizhi and Jayashree's (2021) optimal data flow scheduling technique. Offering a revolutionary method known as energetic optimum arrangement and congestion control in WNs, which can delay the best presentation, accomplishes this. This innovative method restores wireless networks' throughput and speed by modifying the scheduling plan with a virtual adaption model. To make the scheduling less complicated, each slot is divided into smaller slots. To further ease congestion, the tiny slots are split into micro slots. Based on the scale of emergency, virtual rate modification is done in a variety of methods for the different flow connections that exist inside the network system in order to represent individual priority. When compared to other research techniques, this technique achieves the best delay in terms of improved performance ratio [10].

A new Extended Kalman filtering and Bandwidth (CSEKB) was developed by Wang et al. in 2020. By constructing a noise perception factor, the CSEKB is able to discern between different types of packet loss and effectively observe the bandwidth fluctuation of wireless networks. The congestion management parameters are modified in accordance with the congestion factor to enhance the act of the wireless network. Network Simulator 3 (NS3) was used to put the CSEKB into practice, and it was compared with existing approaches. The CSEKB can enhance average throughput and link utilization through intensive simulation studies and perform congestion regulator based on the precise forecast of available bandwidth [11].

To improve the transmission performance, Li et al. (2019) presented a Delay-Based Congestion Control Algorithm (DBCCA. The algorithm that was created essentially consists of two phases. A near-optimal rate circulation vector is then attained using a genetic algorithm after first formulating a controlled optimization problem to reduce the delay transformation between various paths. Furthermore, alter the congestion windows depending on the collected rate allocation vector and the round-trip duration to spread traffic across each pathway. DBCCA effectively balances throughput and latency to maximize mobile traffic transmission in heterogeneous connectivity situations. According to experimental findings, DBCCA moves some traffic from advanced loss paths to lower loss ones, suggestively increasing throughput [12].

3. Proposed Methodology

A wireless network's available bandwidth can fluctuate erratically and dynamically depending on the association status, media rivalry, signal quality, and additional numerous unknowable influences. The HMM-IANFIS is created to forecast the bandwidth rate and manage congestion. A wireless network's available bandwidth can fluctuate erratically and dynamically depending on the association status, media rivalry, signal quality, and additional numerous unknowable influences. The HMM-IANFIS is created to forecast the bandwidth rate and manage congestion.

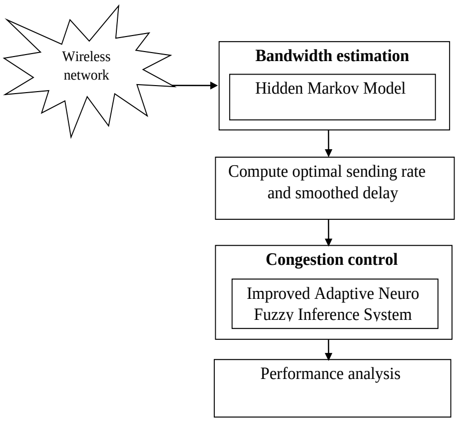

Fig .1. Flow diagram of the proposed work

3.1. Network model

Undertake that the initial period of the wireless network is the beginning of individual bit period of the sent data. When dual neighboring probe packets P1 and P2 attain somewhere at router rapid succession while there are data packets waiting in the route. At the receiving end, P1 and P2 have a time difference of g_{out}.

$$g_{out} = g_B + \frac{B_f \times g_{in}}{C_{bott}} \tag{1}$$

Where, g_B stands for the output link transmission delay. The bottleneck link's bandwidth is denoted by the acronym C_{bott}. When P1 and P2 attain at the router, B_f represents the cross traffic during that time period. It is assumed Lp is.

$$g_B = \frac{L_p}{C_{bott}} \tag{2}$$

A number of equal-sized packet arrangements were utilised since transmitting a single statistics packet cannot effectively capture the typical worth of the cross traffic due to the fact that the actual network cross traffic is constantly changing. Therefore, the value of g_{out} can be sorted into Equation (3).

$$g_{out} = \frac{1}{C_{bott}}(L_p + B_f \times g_{in}) \tag{3}$$

3.2. Bandwidth estimation using Hidden Markov Model

Available bandwidth, as an important indicator of network performance, can be thought to provide us with the reference on monitoring network behaviour, improving the efficiency of data transmission and network planning. A WN's available bandwidth can fluctuate erratically and dynamically. However, it is extremely important to the design of the CCA because it is a crucial parameter in congestion management and QoS assurance. Therefore, three key models for bandwidth prediction were first examined in order to accurately and quickly predict the network's available bandwidth. The available bandwidth is determined by the Hidden Markov Model (HMM), which then implements congestion control as necessary.

3.2.1. Investigation of Accessible Bandwidth

A WN cannot have an idle link at all times. As a result, cross traffic is the amount of link capacity that is being used at a given moment, while available bandwidth is the amount of link capacity that is still available. There are only two link states at any given time: the "idle" state and the "used" state.

When the system is in a steady state, it is expected that its irritable circulation will remain relentless for the duration of $(t, t+\tau)$, and $\rho_i(t)$is definite as the link's prompt utilisation state at time t; it is 0 when the link is idle and 1 when it is in use, as indicated in equation.

$$\rho_i(t) = \begin{cases} 0 & link\ i\ \text{“}idle\text{”} \\ 1 & link\ i\ \text{“}used\text{”} \end{cases} \tag{4}$$

The average utilisation rate $\rho_i(t)$ of link i can be intended since the prompt state of link i, as exposed in equivalence.

$$\rho_i^\tau(t) = \int_t^{t+\tau} \rho_i(t)\, dt \tag{5}$$

As a result, the cross traffic $B_i^\tau(t)$ is shown in equation

$$B_i^\tau(t) \equiv C_i * \rho_i^\tau(t) \tag{6}$$

Obviously, the available bandwidth $AB(t)$ is the unexploited part of the C. $AB(t)$ can be defined in equation

$$AB(t) = C_i * (1 - \rho_i^\tau(t)) \tag{7}$$

After examining the accessible bandwidth of a single link, A^τ of different paths $P(l_1, l_2, \cdots, l_n)$ within (t, t + τ) can be demarcated.

$$AB = \min_{i=1\ldots n} (C_i * (1 - \rho_i^\tau(t))) \tag{8}$$

The available bandwidth levels (ranges) are represented by discrete hidden states X in this Hidden Markov Model (HMM), and the probing packet pair dispersions are represented by discrete observation variables ξ.

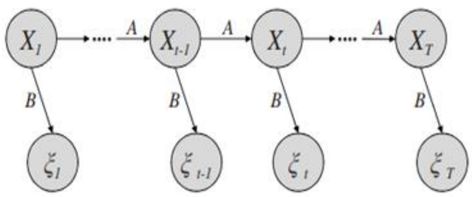

Fig. 2. Hidden Markov Model (HMM)

A specific observation has a probability B that it was produced by a specific concealed state. The probabilities listed in the transition probability matrix A control the transition between states. This prototypical, which is improved with each new reflection, is cast-off to identify the most likely state arrangement $(X1, X2, \ldots, XT)$ inferred to be in charge of the data collected during T.

The HMM comprises of the subsequent five essentials:

1) State count in the prototypical (N). The better the accuracy, but the extended it takes to make an estimate, the higher this number. $S = S_1, S_2, \ldots, S_N$, where the available bandwidth level increases from S_1 to S_N, defines the set of states. X_t stands for the state at time t.

2) Various remark signs per state, number (M). These are all the consequences that a state could have. Specifically, the group of symbols that represent the detected dispersions as determined by the probing sample technique. Despite the fact that this number can be altered in the model, in Trace band's avoidance employment it is set to ten symbols, represented by V = $v_1, v_2, \ldots, v_{10}$. The continuous observed values ϵ of are grouped using these symbols, which are decimal numbers from 1 to 10, in the intervals [0,0.1], [0.1,0.2], and [0.9,1]. Every reflection is changed from a continuous to a discrete symbol by:

$$\xi_t = [M \times |1 - \epsilon_t|] \tag{9}$$

3) Probability matrix for state transitions (A). A = $[a_{ij}]$, where $a_{ij} = P(X_{t+1} = S_j \mid X_t = S_i)$, $1 \leq i$. Only the three main diagonals remain as unknown elements in the matrix because only one-step migrations among states are feasible:

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & 0 & \ldots & 0 \\ a_{2,1} & a_{2,2} & a_{2,3} & 0 & \vdots \\ 0 & \ddots & \ddots & \ddots & 0 \\ \vdots & 0 & a_{N-1,N-2} & a_{N-1,N-1} & a_{N-1,N} \\ 0 & \ldots & 0 & a_{N,N-1} & a_{N,N} \end{bmatrix} \tag{10}$$

Small values of ξ are anticipated to be caused by a heavily loaded network and are consequently more likely to be produced by a small quantity state, and vice versa.

4) Probability Observation Parameter (B): It is calculated based on number of observations received from multiple time and execution time of each packet rate. The simulation calculation as follows, ξ_t is produced by each state from the set S. More specifically, B = $[b_j(\text{m})]$ where $b_j(\text{m})] = P(\xi_t = v_m | X_t = S_j)$ for $1 \leq m \leq M$ and $1 \leq j \leq N$:

$$b_{s_1} = [P(\xi_1/s_1), \ldots, P(\xi_M/s_1)]$$

$$b_{s_2} = [P(\xi_1/s_2), \ldots, P(\xi_M/s_2)] \ldots\ldots$$

$$b_{s_N} = [P(\xi_1/s_N), \ldots, P(\xi_M/s_N)] \tag{11}$$

5) Probabilities of the initial state (Π). The probability that each state is the beginning in the state arrangement that produced the remarks are represented in this vector. When $1 \leq i \leq N, \Pi = [\pi_i]$ with $\pi_i = P(X_1 = S_i)$. The final three likelihoods are typically written as $\lambda = (A, B, \Pi)$ to signify the model's entire set of parameters.

3.3. Congestion control using Improved Adaptive Neuro Fuzzy Inference System (IANFIS)

Wireless networks can benefit from the HMM's characteristic, and a technique for estimating their available bandwidth is suggested. Additionally, in the following stage, congestion avoidance is based on the prediction result. The network's current level of congestion would then be assessed in this section using the expected bandwidth value.

3.3.1. Compute the optimal sending rate V_{opti}

The sender is required to keep track of the round-trip delay Rtt and the congestion window size cwnd whenever it gets an Acknowledge (ACK). Additionally, Rtt_{min} stores the shortest possible round-trip delay, while Equation V_{opti} defines the ideal transmission rate (12).

$$V_{opti} = \frac{cwnd}{Rtt_{min}} \tag{12}$$

3.3.2. Calculate the smoothed delay Rtt_{smo}

The round-trip delay Rtt is smoothed using the mean filtering technique in order to remove noise interference. First, create a template for Rtt that includes all of the most recent delay values, Rtt_{all}. The average of all interruptions in the prototype is then used to define the smoothed delay Rtt_{smo}, as shown in Equation (13).

$$Rtt_{smo} = \frac{Rtt_{all}}{n} \tag{13}$$

The smoothed delay Rtt_{smo} can then be used to derive the actual transmission rate V_{act}, as indicated in Equation (14). It is important to remember that in order to fully utilise network resources

$$V_{act} = \frac{cwnd}{Rtt_{smo}} \tag{14}$$

Congestion control is carried out in this suggested work using IANFIS. Here, the expected bandwidth value and perception factor of a packet backlog would be used to assess the network's present state of congestion.

ANFIS's nature works in a way that a portion of its nodes are also adaptive, which means that their outputs are determined by the parameters that fit into each node [13–15]. The ANFIS model's architecture is exposed in Figure 3.

It is not possible for multiple rules to share same outputting membership function. The quantity of regulations and involvement duties must be identical. To demonstrate the construction, we proposed two rules with the combination of IF-THEN using first order Surgeon model discussed

Set-Rule $_{(1)}$: $IF\ x\ is\ A_1\ AND\ y\ is\ B_1, THEN$

$f_1 = p_1x + q_1y + r_1$

Rule $_{(2)}$: $IF\ x\ \ is\ A_2\ AND\ y\ is\ B_2, THEN$

$f_2 = p_2 x + q_2 y + r_2$

Where,

From the above rule x,y are the inputs, A and B are the Fuzzy set values, p,q,r are the parameters

f_i- outputs .

By using the appropriate Membership Functions, the degree of membership can be estimated (MF). Many different subscription criteria are used in fuzzy algebra. In this proposed research work, Sigmoid Membership Function (MSF) have been used to develop fuzzy inference systems.

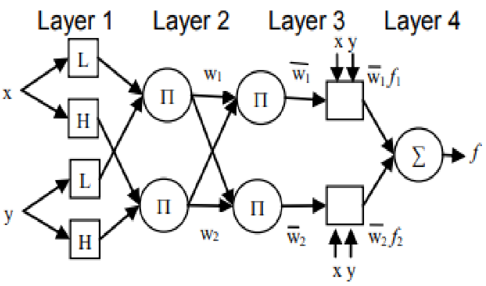

Fig .3. Architecture of ANFIS

Layer 1: In the initial layer, entirely the nodes are adaptive nodes. Here, the actual optimal sending rate V_{opti} and smoothed delay Rtt_{smo} are considered as an input and it is given to first layer. The fuzzy membership grade is the outcome of Layer 1:

$$O_{1,i} = \mu_{Ai}(\mathrm{x})\,, i = 1,2 \qquad (15)$$

$$O_{1,i} = \mu_{Bi-2}(\mathrm{y})\,, i = 3,4, \qquad (16)$$

Where, x and y are the contributions to node i, and A_i and B_i are the linguistic labels (high, low, etc.). $\mu_{Ai}(x)$ and $\mu_{Bi-2}(y)$ can assume any fuzzy association denotation. For instance, if the Sigmoid Fuzzy Membership Function (SFMF) is employed, $\mu_{Ai}(x)$ is given by

$$\mu_{Ai}(x) = \frac{1}{1+e^{-a_i(x-c_i)}} \qquad (17)$$

$$\mu_{Bi}(y) = \frac{1}{1+e^{-a_i(y-c_i)}} \qquad (18)$$

The input is continuously monotonically mapped to a value between 0.0 and 1.0. where the set assumption parameters are a_i and c_i. It is suitable for conveying ideas like "extremely enormous" or "very negative" since, regardless on the parameter's sign, it is fundamentally open to the right or the left.

Layer 2: The nodes in Layer 2 are standard network. This layer uses fuzzy operators and fuzzifiers the inputs by means of the AND operator. They are noticeable with $\prod$ the symbol. This layer's output can be articulated as the following:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y),\ i = 1,2 \qquad (19)$$

From the Eq.19 results are rules of firing strength obtained from iterative measurements.

Layer 3: In Layer 3, the nodes are similarly fixed nodes denoted by N, signifying that they serve as normalizers for the firing concentrations from Layer 2. This layer's output can be expressed as the following:

$$\mathrm{O}_{3,\mathrm{i}} = \overline{\mathrm{w}}_{\mathrm{i}} = \frac{\mathrm{w_i}}{\mathrm{w_1+w_2}}\,, i = 1,2 \qquad (20)$$

The values of the relevant layers' power spectral densities are w_1 and w_2, respectively. These power spectral density values are used to determine the transmitter antenna powers.

Layer 4: The Layer 4 connectors are flexible. Only the standardized weight boosted by a first order polynomial is output from each node in this layer.

$$\mathrm{O}_{4,\mathrm{i}} = \overline{\mathrm{w}}_{\mathrm{i}} f_i = \overline{\mathrm{w}}_{\mathrm{i}}\,(p_i x + q_i y + r_i), i = 1,2, \qquad (21)$$

Where, $\mathrm{w_i}$ is the productivity of Layer 3, and $\mathrm{p_i}$, $\mathrm{q_i}$, and ri are the resultant parameters

Layer 5: There is solitary one immobile node in Layer 5 that is marked with the letter P. The totaling of all received signals is accepted out by this node. The model's overall output is provided by

$$\mathrm{O}_{5,\mathrm{i}} = \sum_i \overline{\mathrm{w}}_{\mathrm{i}} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (22)$$

The congestion status is the output of the layer 5.

Furthermore, it is important to determine the perception factor Fnp transmission rate falls short of the ideal transmission rate V_{opti}. Congestions are first identified based on the features of the packet and subsequently on the weight value under various bandwidth conditions. Congestion which will worsen the network's already problematic congestion. As a result, this method offers a foundation for evaluating noisy packet loss, and the new window limitations are set in accordance with this, making the parameter changes more in line with the wireless network's actual circumstances. Additionally, it enhances the transmission performance of wireless networks by lessening the bandwidth loss brought on by a wider window size.

4. Experimental Results

The goal of the simulation is to evaluate the effectiveness of the suggested methodology, and the few quantitative metrics used for this evaluation are shown below.

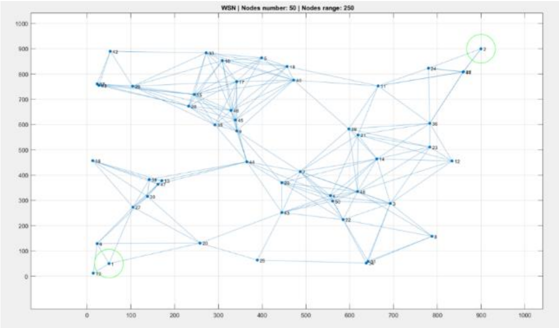

Fig. 4. Nodes are randomly deployed with range 250

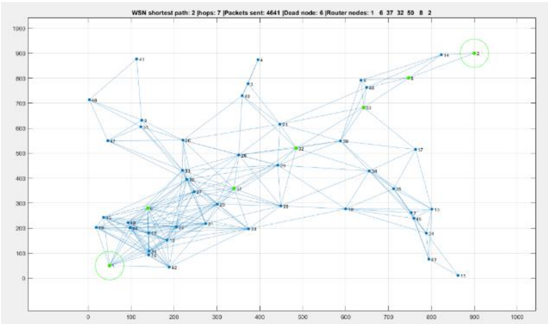

Fig. 5. Packet transmission in WN through shortest path – Phase 1

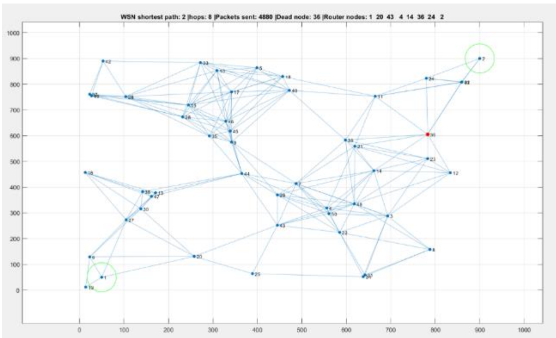

Fig. 6. Packet transmission in WN through shortest path – Phase 2

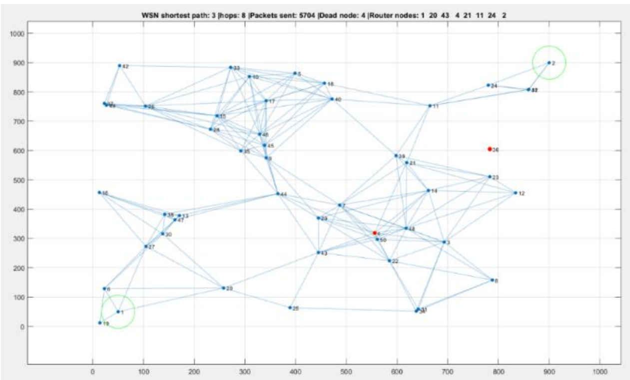

Fig. 7. Packet transmission in WN through shortest path – Phase 3

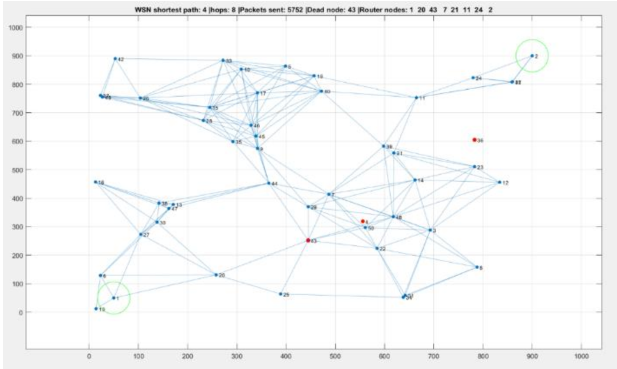

Fig. 8. Packet transmission in WN through shortest path – Phase 4

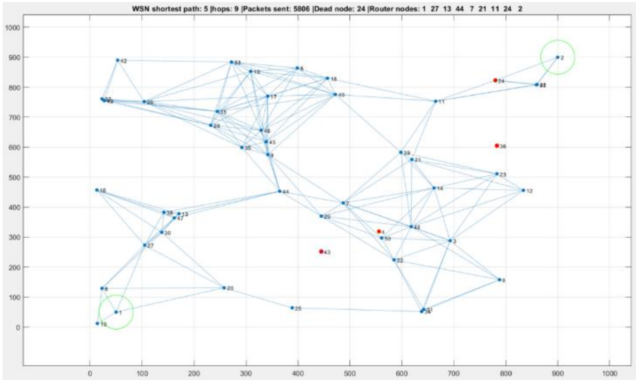

Fig. 9. Packet transmission in WN through shortest path – Phase 5

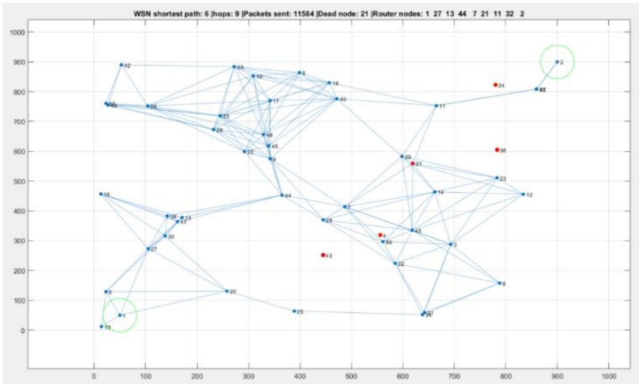

Fig. 10. Packet transmission in WN through shortest path – Phase 6

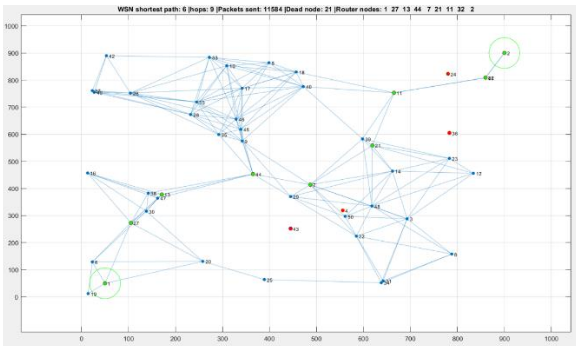

Fig. 11. Packet transmission in WN through shortest path – Phase 7

The metrics used to evaluate the performance are given below:

(i) Packet delivery ratio: PDR is packet delivery ratio which is calculated based on total number of packets send and received from one source to another. In this case we found greater number of packets to be delivered from multiple intended areas or network. Figure 12 shows that simulation result of PDR connected with evaluation of performance indexes. From the results it shows that we got better and improved results.

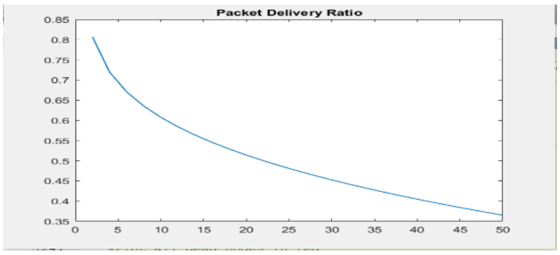

Fig. 12. Packet Delivery Ratio

(ii) Throughput: It is obtained as in a particular second number packets successfully transmitted or completed the transaction. In a well-designed Network, the value of throughput should be high, and if it is subject to an attack of any kind, the throughput value drops dramatically. The suggested protocol's packet delivery ratio has been trending upward, which indicates a significant increase in throughput. Throughput has increased by approximately double (Figure 13). With the different numbers of nodes, the suggested protocol generally exhibits positive trend in all of the metrics.

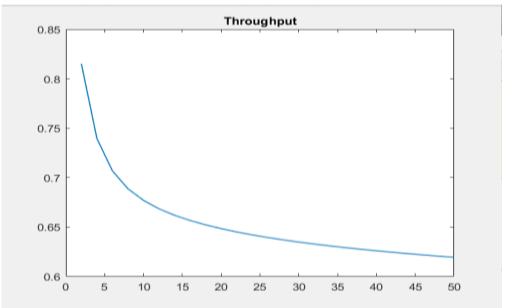

Fig. 13. Throughput

5. Conclusion

For predicting the available bandwidth rate and managing congestion in wireless networks, the suggested system developed a Hidden Markov Model with Improved Adaptive Neuro Fuzzy Inference System (HMM-IANFIS). The system made use of the HMM feature that, under the right circumstances, may minimise estimation error and accurately predict the amount of available bandwidth for WN. Lastly, the wireless network's service excellence is enhanced, and the system's general stability is guaranteed. The findings show that the CSEKB has better convergence, accuracy, throughput, packet delivery ratio, and higher utilization, and can predict network bandwidth and control congestion in wireless networks.

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