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Minimizing End-to-End Delay and Maximizing Reliability using Multilayer Neural Network-based Hamming Back Propagation for Efficient Communication in WSN

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***Abstract*—**Wireless sensor network (WSN) comprises number of spatially distributed sensor nodes for monitoring the physical environment conditions and arranging the gathered data at central location. WSN gained large attention in medical field, industry, military, etc. However, congestion control mechanism for communication between sensor nodes failed to consider the end-to-end delay features. In addition, it failed to handle reliability and not achieved the data concurrency. In order to address the above mentioned problems, Multilayer Neural Network-based Hamming Back Propagation (MNN-HBP) technique is introduced for efficient communication in WSN. In MNN-HBP technique, Amorphous View Point Algorithm is introduced for sensor node initialization for efficient communication in WSN. Amorphous View Point Algorithm used time of arrival to measure the time distance between the sender node and receiver node. After that Hamming Back Propagation Algorithm is used to identify the current location of the sensor nodes for minimizing the end-to end delay and improving the reliability. Each sensor node compares their distance with the neighbouring sensor nodes distance to identify the associated error. When the distance is higher, the associated error is higher and propagates error back to other sensor nodes in the previous layers. The process gets repeated until the communication established between source sensor and lower associated error nodes. By this way, efficient communication is carried out with higher reliability and minimum end-to end delay. Extensive simulation are conducted to illustrate the efficiency of proposed technique as well as the impacts of network parameters on end-to-end delay, reliability and data packets successful rate with respect to data packet size and number of data packets.

Keywords: *Wireless sensor network, Amorphous View Point, congestion control, Hamming Back Propagation, associated error.*

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1. INTRODUCTION

Wireless sensor network are the network of devices that communicate the information collected from monitored field by means of wireless links. Wireless Sensor Network is extensively employed in different areas for surveillance and monitoring in agriculture as well as habitat monitoring. An initial constant congestion window (ICCW) mechanism was introduced in [1] to control the congestion of bottleneck links. ICCW handled sending rate for utilization of link capacity through injecting threshold values (SSTμ, SSTF) in the TCP procedure.

ICCW mechanism was described for improvement of TCP at slow start and congestion avoidance phases. TCP handled with size of congestion window (CWND) improved the performance correspondingly after receiving the ACK. The congestion window extends gradually with one packet to initialize the congestion window with number of packets in place of one packet. However Congestion control mechanism for fast communication between sensor nodes did not consider end-to-end delay aspects. In addition, it failed to handle the reliability and not achieve data concurrency.

In order to address the above mentioned drawbacks, Multilayer Neural Network-based Hamming Back Propagation (MNN-HBP) technique is introduced for efficient communication in WSN. The main contribution of the work is given below:

- To measure the time distance between sender node and receiver node using Time of Arrival technique for Amorphous View Sensor Node Initialization model
- To identify the current location of the sensor nodes using Hamming Back Propagation algorithm for efficient communication in Multilayer Neural Network Localization model

The paper is organized as follows. In Section 2, we discuss some related work in efficient communication in WSN. In Section 3, the proposed Multilayer Neural Network-based Hamming Back Propagation (MNN-HBP) technique is discussed with the algorithm and block diagram. In Section 4, experimental analysis is provided. In Section 5, a simulation setting of MNN-HBP technique is presented and detailed discussion is provided with table and graph. The paper concludes with concluding remarks in Section 6.

2. RELATED WORKS

Wireless sensor networks (WSN) have tens or hundreds of sensor nodes. Nodes sense the information and transmit their data to the base station through wireless

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communication channel. Communication protocols for WSNs hare introduced to support large number of nodes. Several research works were carried out by different researchers in the area of efficient communication in WSN. A distributed event-triggered communication was carried out in [2] for time synchronization. The clock feature of every node was considered as discrete-time second-order dynamics. Every node in network identified whether and when to transmit their states to neighbors depending on event trigger mechanism. But, event-triggered algorithm for time synchronization failed to improve the communication performance due to noise and delays.

The designed technique examined the conditions resulting in the congestion of communication channel with nodes configuration parameters like transmission time intervals, data packet generation rate and transmitter output power level in [3]. Time intervals configuration get influences over the energy consumption and communication channel occupation. However, time intervals were not minimized arbitrarily as they affect the communication channel activity. DCRL-WSN was introduced in [4] with ball-shaped extended bound to inexact estimated location of every target node. A new certainty principle was employed for estimation to each target node. With the extended bounds for target nodes and communication ranges of anchor nodes, bounding box area was computed for every target node by addressing the two constrained convex optimization issues iteratively. However, DCRL-WSN failed to perform cooperate in networks with less number of anchor nodes.

A cross-layer scheme was introduced in [5] to manage the video streaming over wireless sensor networks. The starting point was employed to present carrier sense aware disjoint multi-path routing protocol and to transmit efficiently video. The designed protocol managed with application layer to present the frame-aware solution to allocate high priority to essential frames. But, the node localization was not carried out using cross-layer scheme. An analytical expression was introduced in [6] for indentifying the optimal clusters when the sensing area was divided into hexagonal and voronoi clusters. The effect of data aggregation ratio, position of base station on overall energy consumption was examined through case studies. A channel-aware methodology was introduced in [7] for relay nodes (RNs) pipeline inspection in WSNs. A path loss model was employed for radio propagation over transmission media. A path loss model was introduced for optimum placement of RNs to reduce the energy utilization of sensor nodes.

ReDAST scheme was introduced in [8] for reliable and efficient data acquisition in WSN in existence of the transfaulty nodes. Because of transfaulty actions, sensor node isolated from network. Temporary node isolation resulted in development of dynamic communication holes in network form. An integrated and energy efficient protocol was introduced in [9] for Coverage, Connectivity, and Communication (C3) in WSNs. C3 protocol employed the received signal strength indicator to partition the network into virtual rings, to describe clusters with cluster heads at discontinuous rings, to describe the dings inside cluster and to detect the redundant nodes.

An In-network compression and Multiple Query Optimizations (MQO) based approach was designed in [10] with optimization of multiple queries at base station and data compression at individual nodes leading to the quantitative reduction in communication traffic. Cooperative, Simultaneous Localization and Mapping (CSLAM) was introduced in [11] for efficient communication in WSN. Centralized and distributed map merging techniques was designed in WSN-based CSLAM. In addition, packet delays and losses performance was not improved in CSLAM. A balance energy-efficient and real-time with reliable communication (BERR) protocol was introduced in [12] for wireless sensor networks (WSNs). The designed protocol improved joint real-time results, energy efficiency and reliability. In BERR, node transmitted data packets to the sink node and calculated the energy cost and hop count value to the sink node.

A new method was introduced in [13] to identify appropriate forwarding node for transmission. The forwarding node is initiated depending on the power level of transmitter node. The forwarding node was selected where the distance to destination was lesser compared to additional neighbor nodes of transmitter node. An optimized Congestion management protocol was introduced in [14] for HWSNs. The protocol has two stages. Active Queue Management (AQM) scheme was introduced to reduce the congestion and present the quality of service (QoS). The designed scheme employed separate virtual queues on one physical queue to accumulate input packets from every child node depending on importance and priority of source traffic.

Based on aforementioned issues like higher end-to-end delay, lesser reliability, lesser data packets successful rate, an effective Multilayer Neural Network-based Hamming Back Propagation (MNN-HBP) technique is introduced.

3. METHODOLOGY

With availability of many efficient communication techniques in WSN, delay and reliability are the major parameters needs to be discussed. Let us consider 'n' number of sensor nodes distributed in a random way. It is deployed in '$m * n$' square area that is represented in the form of graph '$G = (V, E)$' within the transmission range 'R'. The network consists of 'n' number of sensor nodes denoted as vertices '$V = \{v_1, v_2, \dots, v_m\}$' and edges '$E = \{e_1, e_2, \dots, e_n\}$' denoting the links between the sensor nodes. The main objective of this work is to reduce the end-to-end delay and increase the reliability using Multilayer Neural Network-based Hamming Back Propagation (MNN-HBP) technique. The architecture diagram of MNN-HBP technique is described in figure 1.

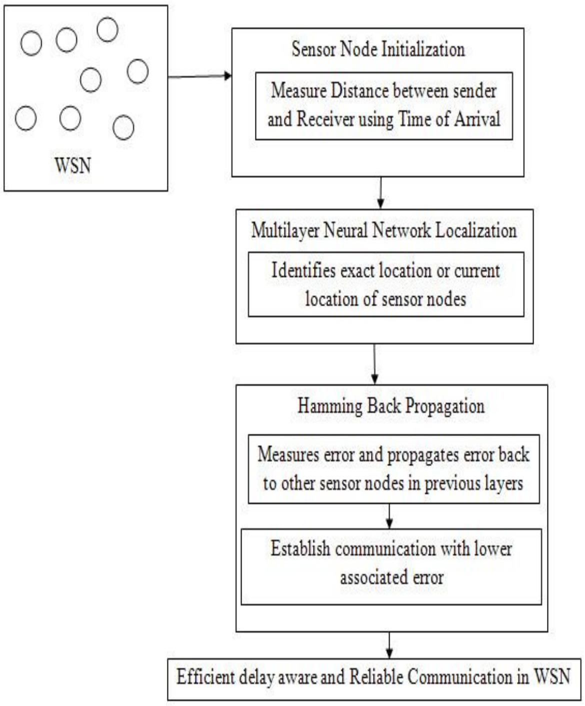

Figure 1. Architecture Diagram of MNN-HBP Technique

Figure 1 explains the architecture diagram of MNN-HBP Technique. MNN-HBP Technique comprises three models, namely Sensor Node Initialization model, Multilayer Neural Network Localization model and Hamming Back Propagation model for efficient communication in WSN. In first model, Distance between sender and receiver are measured using Time of Arrival. After that in second model, exact location or current location of sensor nodes is identified. Finally, establish the communication with lower associated error nodes. By this way efficient communication process is carried out. The brief explanation of model is described in below sub-sections.

3.1Sensor Node Initialization Model

In MNN-HBP technique, the network initialization process is carried to perform efficient communication between nodes in WSN. For performing the sensor node initialization, Amorphous View Point algorithm is used. The main aim of the Amorphous Viewpoint algorithm is to calculate the hop distance between two nodes instead of the linear distance between them. Amorphous view point algorithm comprises three steps.

- Network Mean Interval Calculation
- Minimum Hop Count Calculation
- Maximum Likelihood Estimation

In Amorphous Viewpoint algorithm, the communication radius of each sensor node is measured. There exists the large deviation, if the communication radius of node is calculated as the single hop. After measuring the communication radius, the mean interval of one hop is calculated in order to select and initialize the hop node for efficient communication in network with minimum end-to-end delay. Let us consider that, 'a' be the sensor node and 'c' be the beacon node in the network. Time of Arrival technique is defined as the travel time of signal from beacon node to a sensor node. Time of arrival employs the absolute time of arrival at particular base station rather than measured time difference between the sender and receiver node. The distance is computed from time of arrival with known velocity of hop node. For finding the mean interval, hopsize 'HS' needs to be calculated and it is given as,

$$HS_a = \frac{\sum_{c\neq a}\sqrt{(x_a-x_c)^2+(y_a-y_c)^2}}{\sum_{c\neq a} h_{(a,c)}} \quad (1)$$

From (1), (x_a,y_a) and (x_c,y_c) are the coordinates of the nodes 'a' and 'c'. '$h_{(a,c)}$' denotes the hop between node 'a' and 'c'. After calculating the average hop-size, each beacon node transmits its hop-size over the network. After receiving the hop-size, all nodes determine the physical distance to the beacon. It is calculated as,

$$d_{ac} = HS_a * h_{(a,c)} \quad (2)$$

From (2), the mean interval calculation of two nodes is carried out. Every beacon node sends messages to the unknown nodes. The minimum hop from the node 'a' to 'c' are formulated as,

$$S_{a,c} = \frac{\sum_{b\in n(i)} h_{(b,c)} + h_{(a,c)}}{|n(i)|+1} \quad (3)$$

From (3) '$S_{a,c}$' represents the minimum hop from node 'a' to node 'c'. '$h_{(b,c)}$' denotes an integer hop from unknown node 'b' to the beacon node 'c'. '$h_{(a,c)}$' symbolizes an integer hop from unknown node 'a' to the beacon node 'c'. '$n(i)$' refers the neighbor nodes around the unknown node 'i'. '$|n(i)|$' denotes the number of neighbor nodes around the unknown node. The maximum likelihood distance estimation process is carried out to find the sensor nodes with minimum hopcount value for efficient communication. Maximum likelihood estimation (MLE) is the process of estimating the parameters of statistical model with the observations. MLE find the parameter values that increase the likelihood function with the observations and it is given by,

$$\theta_{S_{a,c}} \in \{\arg\max \mathcal{L}(\theta_{S_{a,c}}, h_{a,c})\} \quad (4)$$

From (4), '$\mathcal{L}(\theta_{S_{a,c}}, h_{a,c})$' denoted the likelihood function. The maximum likelihood sensor nodes ready for communication are initialized in WSN. The algorithmic process of amorphous view point algorithm is given below,

//Amorphous View Point Algorithm
Input: Communication radius, average network connectivity
Output: Measure network mean interval
Step 1: Begin
Step 2: **For** each communication radius with average network connectivity
Step 3: Measure network mean interval
Step 4: Measure minimum hop count
Step 5: Measure maximum likelihood estimation
Step 6: **End** for
Step 7: End

Algorithm 1 Amorphous View Point Algorithm

The above algorithmic process describes the sensor node initialization process for efficient communication in wireless sensor network. Initially, the communication radius of sensor nodes is calculated. After that, the network mean interval is measured for every communication radius. The minimum hop count and maximum likelihood estimation are carried out to reduce the delay for efficient sensor node initialization. After that, the current location of the sensor is identified during Multilayer Neural Network Localization model and Hamming Back Propagation Model.

3.2 Multilayer Neural Network Localization model and Hamming Back Propagation Model

After linking the sensor nodes, the current location of sensor nodes are identified through Multilayer Neural Network Localization model in MNN-HBP technique. Neural network comprises number of neurons organized in the layers that convert an input vector into an output. Every neuron takes an input, applies the non-linear activation function and passes the output to the next layer. Multilayer Neural Network classifier uses the human neuron on the system. Human brain contains hundreds of billions interconnected neurons. Neurons are combined to form the network for sending the information with additional layer through signals. When the link between two neurons is strong, conversion is performed from one neuron to another one. Therefore, multilayer neural network classifier is made up of input layer neurons, hidden neuron and output neurons. The structure of neural network classifier is described as,

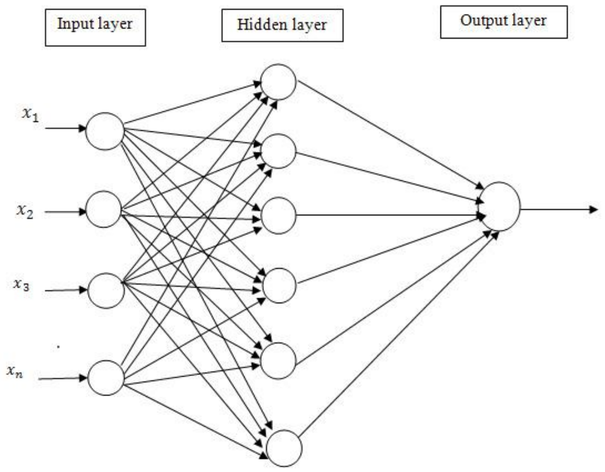

Figure 2.2. Multilayer Neural Network Classifier

Figure 2 explains the neural network classifier with three different layers, namely input layer, more hidden layer and output layer. In multilayer neural network, every node from input layer is connected to the hidden layer and every node from the hidden layer is linked to the output layer. Generally, there is a different weight connected with every connection. Back propagation neural network is supervised learning that varies their weight through propagating from the one layer to another. The main objective of neural network classification based hamming back propagation is to reduce the associated error through propagating back to the other sensor nodes in the previous layers and the process gets repeated until communication established between source sensor and lower associated error.

Hamming back propagation is carried out with the different layers. During the hamming back propagation, patterns in the network are input through neurons. The neurons in the input layer are described through objective function for efficient communication in WSN. The output from input layer is sent through the synaptic weight to the hidden layer in neural network. The hidden layer is a processed layer with the sum function and non-linear activation function. The non-linear activation function employs the sigmoid function due to the soft switching process.

The input layer denotes the sensor nodes pair linked to the multilayer neural network for efficient communication in WSN. Every input is transmitted to the nodes in hidden layer. Hidden Layer collects the weight of all sensor node pairs based on the energy consumption from the input layer. It uses the input values and changing them according to the weight value (w_{ij}). The updated weight value is to transmit into the output layer however it is changed through some weight from the connection between

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the hidden and output layer. Output layer process the information attained from the hidden layer through non-linear activation function and generates a final output.

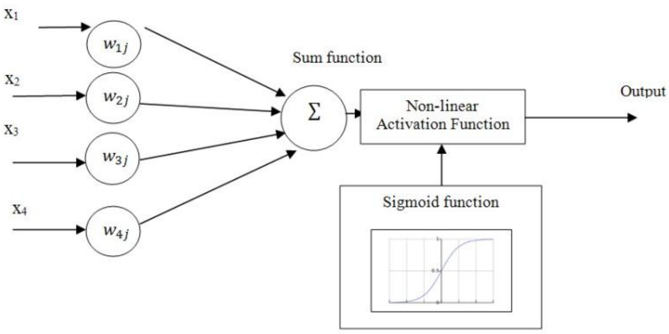

Figure 3. Non-Linear Activation Function

Figure 3 explains the non-linear activation function process. The hidden layer includes two function like sum function and activation function. The activation function used is a sigmoid function to combine the non-linear performance, curved behavior and constant behaviors depending on input value. A sigmoid function is a statistical function with 'S' shaped curve as the sigmoid curve. A sigmoid function exists at negative infinity and positive infinity where output lies between -1 and 1. The sigmoid function is formulated as,

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (5)$$

From (5), sigmoid function is calculated for the neural network classifier. In hidden layer, multiplication of input information with weight is added by the SUM function. SUM is a group of output nodes from hidden layer multiplied with the weights allocated to each input value to attain the single number through sigmoid function. After that, an updated weight between hidden layer and output layer transmitted from hidden layer output to output layer. The output layer is a processing unit with summation function and activation function. In output layer, product of activated output of hidden layer and weight between hidden layer and output layer is added through the summation function. After that, it is transferred to the activation function for finding the exact location of the sensor node to perform efficient and reliable communication in sensor network.

The desired output is evaluated with the obtained output for measuring the error rate. Each sensor node compares their distance with the neighbouring sensor nodes distance to identify the associated error. The associated error is calculated by,

$$\text{Associated Error } (AE) = \text{Predicted distance output } (P_o) - \text{Obtained distance output } (O_o) \quad (6)$$

When the distance is higher, the associated error is higher and it propagates error back to other sensor nodes in the previous layers. The process gets iterated until communication is carried out between the source sensor and lower associated error nodes. Therefore, the learning rate and momentum rate are introduced for gradient fall to find the weight that minimizes the error. The associated error rate between the output layer and hidden layer are calculated as follows,

$$AE = P_o - O_o \quad (7)$$

$$\delta = AE\ O_o\ (1 - O_o) \quad (8)$$

$$\delta = (P_o - O_o)\ O_o\ (1 - O_o) \quad (9)$$

From (7), (8) and (9), associated error rate is computed. 'P_o' denote the predicted output neuron value, 'O_o' symbolizes obtained output through the activation value with the sigmoid function. '$O_o(1 - O_o)$' represent the derivative of sigmoid function in the hidden layer. After that, the synaptic weight is calculated by,

$$\Delta W_{jk} = \eta\ \delta\ I \quad (10)$$

From (10), '$\Delta W_{j,k}$' represents the updated synaptic weight between output layer and hidden layer, 'η' symbolizes the learning factor that denotes the relative variation in synaptic weights and input (I). Consequently, the updated synaptic weight is obtained through multiplying the error with an input. The updated weight is defined as,

$$W_{j,k} + \Delta W_{j,k} \quad (11)$$

The new weight is attained,

$$W_{new} = W_{j,k} + \eta\ \delta\ I \quad (12)$$

From (12), new weight is obtained depending on the original weight and updated synaptic weight. The process gets repeated until the error rate gets minimized. Finally, the exact position of the sensor nodes is located for improving the communication in WSN. The algorithmic process of Hamming Back Propagation algorithm is given below,

// Hamming Back Propagation Algorithm
Input: Initialized sensor nodes
Output: Exact sensor node location for efficient communication
Step 1: Begin
Step 2: Repeat

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Step 3: **For** each sensor node pair
Step 4: Obtain all the sensor nodes in the network
Step 5: Apply non-linear activation function to determine the source node neighbour
Step 6: Calculate the weight based on energy consumption
Step 7: Measure associated error
Step 8: Assign the neighbouring node with minimum distance and minimum associated error
Step 9: **End** for
Step 10: **Until** (Termination conditions not met)
Step 11: End

Algorithm 2 Hamming Back Propagation

Initially, the number of sensor nodes initialized as an input for hamming back propagation algorithm. The number of neurons (i.e sensor nodes) is given to the hidden layer to determine the exact position of the sensor nodes for efficient and reliable communication in WSN. After that, non-linear activation function is used to locate the source node neighbour. The weight value is computed depending on energy consumption of the sensor nodes. Then, the associated error is calculated and assigned to the neighbouring sensor node. The process gets repeated until the termination criteria are satisfied. By this way, efficient communication is carried out among sensor nodes in WSN with minimum end-to-end delay and maximum reliability.

4. PERFORMANCE EVALUATION

The section computes the Multilayer Neural Network-based Hamming Back Propagation (MNN-HBP) technique is implemented in NS2 network simulator. The proposed technique is compared with initial constant congestion window (ICCW) method [1]. To evaluate the performance of MNN-HBP technique, 70 nodes are positioned in network range of 1000 m*1000 m size. The proposed technique uses Random Waypoint Method. The source and destination pair for MNN-HBP technique is placed in random form. In MNN-HBP technique, number of data packet are taken as 10, 20, 30,…, 70. The sensor nodes in the network choose the mobility speed value ranging from 0-30 m/s. The simulation is carried out for MNN-HBP technique with multiple instances of sensor nodes for efficient communication in wireless sensors network. The simulation parametric values for performing experiments are shown in Table 1.

Table 1 Simulation Parameters

Simulation parameter	Value
Simulator	NS 2.34
Protocol	DSR
Number of nodes	10,20,30,40,50,60,70
Simulation time	200s
Pause time	10s
Mobility model	Random Way Point
Transmission range	250m
Network area	1000m * 1000m
Data packets	10, 20,30.40,50,60,70
Mobility speed	1-30 m/s

5. DISCUSSION

In this section, the result analysis of MNN-HBP technique is carried out in comparison with the existing method, initial constant congestion window (ICCW) method [1] in WSN. The data packet size is taken in the range of 100KB and 700KB. The simulation is carried out for 7 times. The metrics used in the evaluations are end-to-end delay, reliability, data packet successful rate, data packet generating rate with respect to data packet size and number of sensor nodes for efficient communication in WSN.

5.1End-to-End Delay (EED)

End-to-end delay is defined as amount of time taken for packet to be transmitted across a network from source to destination. It is measured in terms of milliseconds (ms). It is formulated as,

$$EED = \sum_{i=1}^{n} Time\ (DP_i)_{SN \rightarrow DN} \quad (13)$$

From (13), end-to-end delay is calculated using the data packet with the source node 'SN' and destination node 'DN'. When the end-to-end delay is lesser, method is said to be more efficient. Table 2 describes the tabulation for end-to-end delay.

Table 2 Tabulation for End-to-end delay

Data Packets Size (KB)	End-to-end delay (ms)	
	MNN-HBP technique	ICCW method
100	54	65
200	41	57
300	46	62
400	55	68
500	61	75
600	54	61
700	57	64

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Table 2 describes the end to end delay with respect to data packet size ranging from 100KB to 700KB in simulation area. When the packet size gets increased, the end to end delay also gets changed correspondingly. But, the end to end delay of proposed MNN-HBP technique is comparatively lesser than the existing ICCW method [1]. The graphical representation of the end to end delay is shown in figure 4.

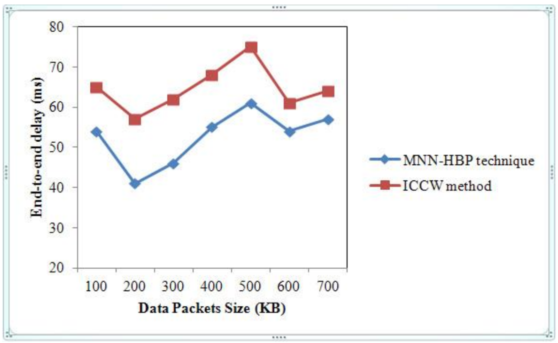

Figure 4 Measure of End-to-end delay

Figure 4 describes the end-to-end delay comparison of the proposed MNN-HBP technique with the existing ICCW method [1]. For conducting the experiments of end-to-end delay, network scenario with data packet size ranging from 100KB to 700KB is taken. When the data packet size is 500KB, proposed MNN-HBP technique produces 61ms delay and existing method produces 75ms delay. From the results, it is observed that end-to-end delay of the proposed MNN-HBP technique varies from 41-51ms. The performance of the end-to-end delay increases with the increase in data packets size but the linearity is not observed because of the topological variations. In MNN-HBP technique, hamming back propagation algorithm performs better in terms of end-to-end delay than existing method [1] by 19%.

5.2Data Packet Successful Rate (DPSR)

Data Packet Successful Rate is defined as the average rate of successful data packets received at the destination over communication channel. It is measured in terms of packets per second (pps). It is given by

$$DPGR = \frac{\text{Number of successful packets received}}{\text{Time}} \qquad (14)$$

From (14), data packet generating rate is measured using the number of data packet with respect to the time period. When the data packet successful rate is higher, method is said to be more efficient. Table 3 describes the tabulation for data packet successful rate.

Table 3 Tabulation for Data Packet Successful Rate

Number of Data Packets (Number)	Data Packet Successful Rate (pps)	
	MNN-HBP technique	ICCW method
10	6	4
20	14	10
30	16	12
40	21	17
50	38	32
60	41	36
70	64	59

Table 3 explains the data packet successful rate with respect to number of data packet ranging from 10 to 70 in simulation area. When the number of data packets gets increased, the data packet successful rate also gets changed respectively. But, the e data packet successful rate of proposed MNN-HBP technique is comparatively higher than the existing ICCW method [1]. The graphical representation of the data packet successful rate is shown in figure 5.

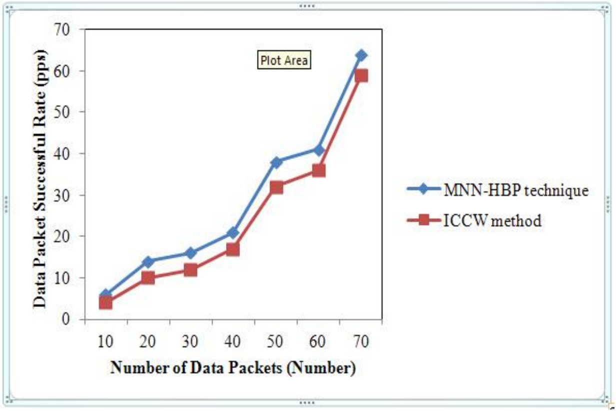

Figure 5 Measure of Data Packet Successful Rate

Figure 5 explains the data packet successful rate comparison of the proposed MNN-HBP technique with the existing ICCW method [1]. For experimental purpose, number of data packets ranging from 10 to 70 is taken in 'X' axis. When the number of data packets is 20, the data packet successful rate of proposed MNN-HBP technique is 16 pps and existing ICCW method is 12 pps respectively. From the results, data packet successful rate of the proposed MNN-HBP technique increases linearly when the number of data packets gets increased. In MNN-HBP technique, hamming back propagation algorithm performs better in terms of data packet successful rate than existing method [1] by 27%.

5.3 Reliability (R)

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Reliability is defined as the probability that the system is operating correctly at given time or the data packets are transmitted to the intended sensor at given time. It is measured in terms of percentage (%).

$$R = \frac{\substack{\textit{Number of data packets correctly} \\ \textit{sent to receiver at given time}}}{\textit{Total number of data packets sent}} \qquad (15)$$

From (15), reliability is calculated using the number of data packet correctly sent to the receiver in a time period. When the reliability is higher, method is said to be more efficient. Table 4 explains the tabulation for reliability.

Table 4 Tabulation for Reliability

Number of Data Packets (Number)	Reliability (%)	
	MNN-HBP technique	ICCW method
10	85	77
20	87	81
30	91	86
40	86	82
50	92	89
60	88	84
70	95	90

Table 4 describes the reliability with respect to number of data packet ranging from 10 to 70 in simulation area. When the number of data packets gets increased, the reliability also gets changed correspondingly. But, the reliability of proposed MNN-HBP technique is comparatively higher than the existing ICCW method [1]. The graphical representation of the reliability is shown in figure 6.

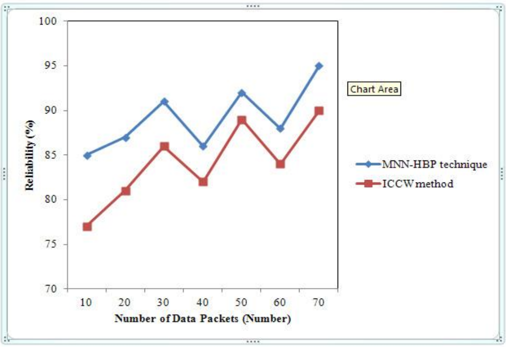

Figure 6 Measure of Reliability

Figure 6 illustrates the reliability comparison of proposed MNN-HBP technique with the existing ICCW method [1]. For conducting the experiments, number of data packets ranging from 10 to 70 is taken in 'X' axis. When the number of data packets is 60, the reliability of proposed MNN-HBP technique is 88% and existing ICCW method is 84% respectively. From above graph, it is clear that reliability of the proposed MNN-HBP technique increases when the number of data packets gets increased but not linearly due to topological variations. In MNN-HBP technique, amorphous view point algorithm and hamming back propagation algorithm improves the reliability rate by 6% than existing method [1].

6. CONCLUSION

A new technique called Multilayer Neural Network-based Hamming Back Propagation (MNN-HBP) technique is introduced for efficient communication in WSN. In MNN-HBP technique, Amorphous View Point Algorithm employed to initialize the sensor node in WSN. Amorphous View Point Algorithm used time of arrival to measure time distance between sender node and receiver node. Hamming Back Propagation Algorithm identifies the current location of sensor nodes for reducing the end-to end delay and for improving reliability. Each sensor node compares their distance with neighbouring sensor node distance to compute the associated error. When the distance is higher, the associated error is higher and it gets propagate back to the previous layers. The process gets repeated until the communication established between source sensor and lower associated error nodes with higher reliability and minimum end-to end delay. Extensive simulations have been conducted to validate the efficiency of proposed technique and provide better performance by reducing the end to end delay and by increasing the data packet successful rate as well as reliability when compared to state-of-the-art works.

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