Journal of Theoretical and Applied Information Technology
15th April 2019. Vol.97. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

DEEP NEURAL CLASSIFICATION AND LOGIT REGRESSION BASED ENERGY EFFICIENT ROUTING IN WIRELESS SENSOR NETWORK

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ABSTRACT

In Wireless Sensor Network (WSN), routing strategies are required for distributing the data from sensor nodes to base station. During the data transmission, the node energy is the key parameter for improving the network lifetime. The conventional routing techniques are developed to perform routing in WSN but it failed to lessen the energy consumption and improve the network lifetime with minimum overhead. In order to overcome the above-said issue, Energy-Efficient Deep Neural Node Classifier based Logit Regressed Routing (EEDNC-LRR) technique is introduced. The main aim of EEDNC-LRR technique is to perform energy efficient routing and increase the reliability of data transmission with maximum network lifetime and minimal overhead. In EEDNC-LRR technique, the sensor nodes are taken to transmit the environmental data. Initially, all sensor nodes have a certain energy level. A sensor node consumes some amount of energy during the sensing of data in WSN. The Deep Neural Node Classifier model is used in EEDNC-LRR technique to classify the node as higher energy nodes and lesser energy nodes based on threshold energy level. From that, the deep neural node classifier model produces the efficient classification results of sensor nodes. This helps to choose the higher energy nodes to reduce the energy consumption and extend the network lifetime while routing the data packets. Subsequently, the higher energy nodes are transmitted to the output layer for efficient routing in WSN. With higher energy nodes, Logit Regression Analysis is carried out to identify the nearest neighbor node through a time of arrival (ToA) to identify the distance between the source nodes and sink node. After selecting the nearest neighbor, the route with a minimum distance between the nodes is discovered for routing in WSN. This in turns, the reliable data packets transmission is achieved with minimum overhead. The simulation is conducted with various parameters namely energy consumption, network lifetime, reliability and routing overhead with respect to a number of sensor nodes and data packets. The simulation results and discussion shows that EEDNC-LRR technique improves the network lifetime, relaibility and also minimize the routing overhead as well as energy consumption.

Keywords: *WSN, Routing, Deep Neural Node Classifier, Threshold Energy Level, Logit Regression Analysis, Nearest Neighbor Node, Time Of Arrival.*

1. INTRODUCTION

A WSN is a wireless network where the sensor nodes are spatially distributed to observe and collects physical circumstances of atmosphere and organize the gathered data and send to base station. WSN is a self-configured network which comprises large number of sensor nodes to monitor the environmental conditions such as temperature, pressure, humidity, wind and so on. The sensor nodes in WSN are liable for sensing and transmitting the sensed informations to sink node. The energy efficient routing is the major concern in the field of the WSN to enhance the network lifetime.

The several techniques have been developed for energy efficient routing but it unable to minimize the routing overhead. Therefore, EEDNC-LRR technique is proposed in this research work. Here, the deep neural node classifier model is used to calculate the residual energy of the sensor node after sensing the data packet information. From that, the higher and

Journal of Theoretical and Applied Information Technology
15th April 2019. Vol.97. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

lower residual energy sensor node is classified and selected for transmitting the sensed data packets. This in turns, energy consumption is minimized and network lifetime is improved in EEDNC-LRR technique. Besides, Logit regression analysis is carried out to identify the nearest energy efficient node based on the node distance measurement. From that, EEDNC-LRR technique creates the path between source node to identified nearest neighbor nodes for transmitting the data packets to the sink node. This helps to increases the reliable data packet transmission and reduces the routing overhead. As a result, the energy efficient routing is effectively achieved using EEDNC-LRR technique in WSN. The routing process in the WSN is described in figure 1.

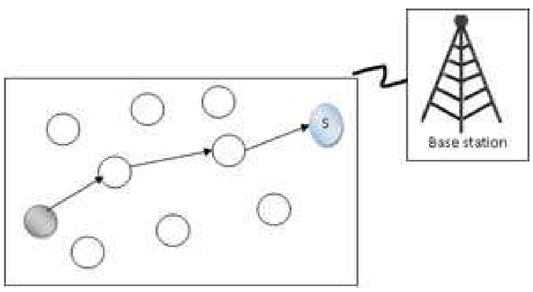

Figure 1. Routing in WSN

Figure 1 shows the routing process in WSN. As shown in figure 1, the source node which is colored by black sent the collected information to the sink node(S) through the neighboring nodes. During the data transmission, the nodes nearby sensor nodes are chosen to perform routing which has higher energy. The several routing algorithms are introduced in this section for energy efficient routing in WSN.

Swarm intelligence based energy efficient hierarchical routing approach called BeeSwarm was introduced in [1]. The approach enhances packet delivery and network lifetime. But, the BeeSwarm approach does not minimize the routing overhead. Distance-And-Energy-Aware Routing with Energy Reservation (DEARER) method was introduced in [2] to obtain energy-efficient routing through the cluster head nodes. The method does not obtain reliable data packet delivery since the neighbor node selection remained unsolved.

The data deliverability of greedy routing was introduced in [3] for efficient data transmission from sensors to the base station. But, the setting of transmission power for every node failed to enhance the energy-efficiency.

Clustering based routing was presented in [4] based on optics inspired optimization. The routing algorithm finds the route from every CH to the base station (BS) based on energy, distance, and node degree. However, the optimization algorithm was not exploited for increasing the coverage area and reducing the number of nodes. Energy-aware simple ant routing algorithm (EASARA) was designed in [5] based on ant colony optimization. The algorithm eradicates low energy routes and improves the network lifetime with lesser delay.

A genetic algorithm based methods were developed in [6] for routing the data packet with minimum energy consumption. The method does not use efficient routing algorithms for a dynamically changed network. In [7], a novel routing algorithm based on the dynamically-allocated hierarchical clustering technique was introduced for improving the network coverage and reducing the control message overhead. The energy efficient routing was not executed to enhance the network lifetime.

In order to improve network lifetime, the position responsive routing protocol was designed in [8]. The protocol lessens the average consumption of the network energy. Though the protocol increases the network throughput, the overhead was not minimized. In [9], energy-efficient paths were identified that lessen energy consumption of the network from the source node to the base station. The algorithm takes more computation time for energy-efficient path selection.

Energy-efficient routing methods based on Genetic Algorithm, Particle Swarm Optimization, and A-Star algorithm were introduced in [10] for maximizing the lifetime of the network. By utilizing the unused sensor nodes, the lifetime of sensor network was not enhanced at a required level. In order to overcome such issues, EEDNC-LRR technique is proposed in WSN to perform energy efficient routing.

The major contribution of the paper is summarized as below,

- ❖ The EEDNC-LRR technique is introduced to improve the network lifetime and improve the data transmission with minimum overhead. The deep neural node classifier calculates energy and residual energy of the sensor nodes in the hidden layers. The classifier set a threshold value and separates the higher energy and lesser energy sensor nodes at the output layer. The higher energy sensor nodes are selected for routing to improve the lifetime of the network.

- ❖ The Logit regression analysis is performed to find the nearest neighbor based on the distance calculation. The distance is computed based on the time of arrival. It is the difference between beacon message transmission time and arrival time of beacon message. The regression analysis is performed with the distance information and finds the nearest node. The source node establishes the route for transmitting the data packets through the neighboring node. This helps to improve the reliable data packet transmission and minimizes the overhead.

The rest of the paper is ordered as follows. Section 2 discusses the related works in the field of energy efficient routing in WSN. Section 3 provides a brief description of the EEDNC-LRR Technique with neat architecture diagram. Section 4 describes the simulation settings. Section 5 provides the numerical analysis, simulation with different parameters. Section 6 gives the finding of the paper. Section 7 provides the conclusion of the paper.

2. RELATED WORKS

The fuzzy ant colony optimization routing (FACOR) technique was introduced in [11] to optimize the energy consumption and increase the network lifetime. The technique does not find the effective solution for solving the routing issues such as routing overhead. A new token-based routing protocol with a multitier cluster-based architecture was designed in [12] to save a large amount of energy to prolong the network lifetime. The architecture failed to accompany multimedia sensor networks.

A Lightweight and Reliable Routing Approach was introduced [13] for obtaining reliable data transmission. The approach failed to choose high energy sensor nodes for balancing the overhead as well as the quality of the routing. A novel Block design-based Asynchronous Neighbor Discovery protocol was designed in [14] for sensor networks. Though the protocol minimizes the energy expenditure, the network lifetime was not enhanced.

A genetic-based routing algorithm was introduced in [15] for balancing the energy consumption of the network and effectively increases the data delivery ratio. The algorithm does not obtain reliability in packet delivery from source to sink node. An improved artificial bee colony algorithm was designed in [16] to reduce the node energy consumption and enhance the network lifetime. The algorithm also guarantees the network connected reliability but it failed to lessen routing overhead.

Energy Efficient Cross-Layer based Adaptive Threshold Routing Protocol was introduced in [17] for WSN to prolong the network lifetime. But it failed to improve the reliable data packet communication in WSN. A centralized multi-objective Pareto optimization technique was introduced in [18] to improve the throughput and minimize the energy consumed by the sensor node. The technique failed to find the optimal transmission energy for each sensor node.

An improved Hierarchical Agglomerative Clustering approach was designed in [19] for energy efficient routing. The clustering approach failed to find the energy-efficient node for enhancing the network lifetime. A novel routing algorithm in energy harvesting sensor networks was introduced in [20] to minimize the energy consumption and prolong network lifetime. Though the method considers the residual node energy, the reliability of the data transmission remained unsolved.

The certain issues are identified from the above literature such as high routing overhead, lack of reliable packet delivery, minimize the network lifetime, more computation time during the energy efficient routing in WSN. To overcome above said existing issues, proposed EEDNC-LRR technique is designed. EEDNC-LRR technique is employed to select the maximum Residual nodes after performing the sensing process. Deep neural node classifier is applied in EEDNC-LRR technique to classify the nodes as higher and lower energy nodes by considering threshold value for performing routing process. This reduces energy consumption and increases the network lifetime. In addition, Logit Regression Analysis is employed to choose the energy efficient node in the network. This in turns, reliable packet delivery is achieved with lower overhead. Therefore, EEDNC-LRR technique is required in WSN to perform efficient reliable routing.

3. ENERGY EFFICIENT DEEP NEURAL NODE CLASSIFIER BASED LOGIT REGRESSED ROUTING IN WSN

WSN is structured by a small sensor node communicating over wireless links without any fixed structure. Each sensor node has limited battery power for the sensed data processing. Therefore an efficient technique is introduced for the purpose of improving energy efficiency in the routing process. Based on this motivation, the Energy Efficient Deep Neural Node Classifier Based Logit Regressed Routing (EEDNC-LRR) technique is introduced in this paper for attaining above said objectives. The EEDNC-LRR technique designed using the system model.

3.1 System model

The WSN is organized in a graph '$G(V,E)$' model where 'V' denotes a number of sensor nodes $SN_i = SN_1, SN_2, SN_3 \dots SN_n$ distributed over a square area of '$N * N$' within the transmission range 'T_r'and 'E' denotes a connection between the sensor nodes in the network. During the routing process, source node routes the data packets '$DP_i = DP_1, DP_2, \dots, DP_n$ to the sink node 'S' through the energy efficient neighboring nodes '$NN_i = NN_1, NN_2, \dots, NN_n$. The neighboring node receives the data packets from the source node and send to the sink node 'S' simultaneously. Before the routing process, energy efficient nodes E_{SN} are identified to enhance the network lifetime as well as obtaining reliable routing in WSN.

3.2 Deep neural classifier and logit regression analysis

An Energy Efficient Deep Neural Node Classifier Based Logit Regressed Routing (EEDNC-LRR) technique is developed to resolve the energy problem since the mobile nodes have limited energy resources. Therefore, the sensor nodes with high energy are selected for executing the efficient routing and maximizing the network lifetime. The energy efficient nodes are chosen among the number of sensor nodes through the Deep Neural Node Classification technique. Deep learning is a class of machine learning algorithms which comprises several layers for processing the inputs. Each consecutive layer exploits the output from the previous layer as input. After the node classification, neighboring nodes are determined through the Logit regression.

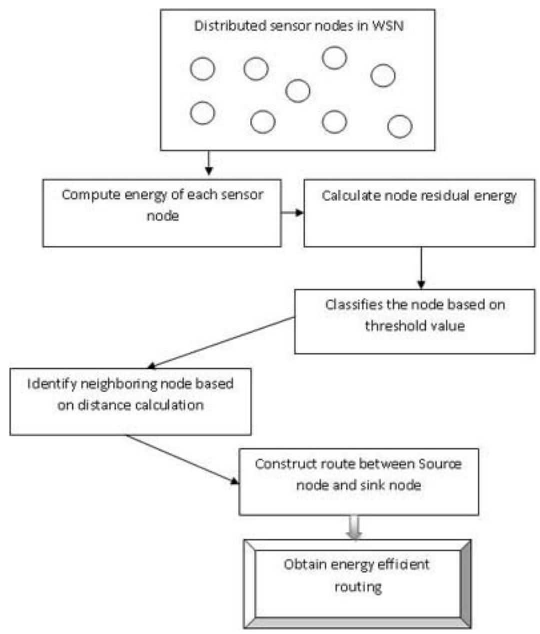

Figure 2 Architecture diagram of the EEDNC-LRR Technique

Based on the regression analysis, the connection between the source node and sink node are established through neighboring nodes for achieving the reliable routing. As a result, efficient deep neural node classifier based logit regressed routing algorithm consumes minimum energy and improves the packet delivery ratio. The architecture diagram of EEDNC-LRR technique is shown in figure 2.

Figure 2 illustrates an architecture diagram of EEDNC-LRR technique to route the data packets with minimum energy consumption. The EEDNC-LRR technique includes the processes namely node classification and data

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

packet routing. The node classification is executed through energy calculation. Initially, the energy and the residual energy of each sensor nodes are computed. Then the deep neural classifier set the threshold to classify the node as higher energy nodes and lesser energy nodes. The higher energy nodes are taken for routing the data packets from the source node to the sink node. During the routing process, the source node finds their neighboring nodes to transmit the data packets. The logistic regression is used for finding the neighboring node and constructs the route between the source and sink node to obtain reliable data packet transmission. These processes are explained briefly in the following subsections.

3.2.1 Energy efficient deep neural node classification

The first process in the design of EEDNC-LRR technique is the sensor node classification based on their energy level. In general, the neural network classifier comprises one input layer, an output layer and at least one hidden layer in between. Each layer consists of the neuron (i.e. sensor nodes) that performs statistical calculations and other operations. Each node in the layers is linked to the other successive layers. This neural network lack of providing the efficient classification results since it has one hidden layer. On the contrary, the EEDNC-LRR technique uses “deep learning” to describe these neural networks for the classification with more layers. The deep neural classifier includes the one input layer, output layer and several hidden layers between them. The numbers of sensor nodes are given as input to the input layer. Each hidden layers performs certain tasks based on the node energy level. The output layer displays an output of the neural ne

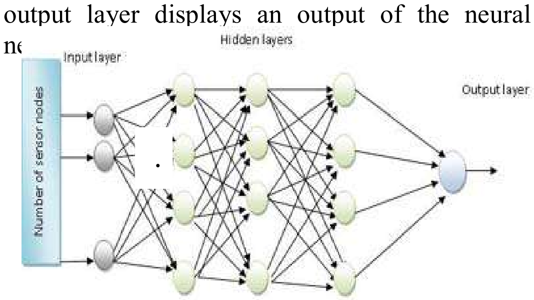

Figure 3 Energy efficient deep neural node classification

Figure 3 depicts the energy efficient deep neural node classification to improve the network lifetime. The above figure clearly shows that the deep neural node classifier with three layers such as one input layer, three hidden layers, and one output layer. The number of sensor nodes $SN_1, SN_2, SN_3 \dots SN_n$ are taken as a sensing device to detect the environmental conditions. These nodes are given to the input layer. Then, inputs are fed into the first hidden layer. In the first hidden layer, calculate the energy for all the sensor nodes. A sensor node consumes a certain amount of energy during the data sensing in WSN. The energy of the each sensor nodes are measured using the following mathematical formula,

$$E_{SN} = p * t \quad (1)$$

From (1), E_{SN} denotes energy of the sensor nodes, p represents a power and t represents a time. The energy of the sensor nodes are evaluated in joule. Then the sensor nodes with their energy values are fed into other hidden layer. In the second hidden layer, the residual energy of the sensor nodes is calculated. The sensor node executes sensing and observing the environment conditions. After the sensing process, the energy of the sensor nodes gets reduced. Residual energy of sensor nodes is calculated to find the remaining energy of the sensor nodes.

$$R_{SN} = E_T - E_c \quad (2)$$

From (2),R_{SN} denotes a residual energy of the sensor nodes, E_T represents a total energy and E_c denotes a consumed energy of the sensor nodes. Residual energy is a remaining energy of the node after sensing the data. Then, these R_{SN} and the sensor nodes are fed into the third hidden layer. In this layer, the classifier model set the threshold value for the residual energy of the sensor nodes.

$$y_i = \begin{cases} if\ R_{SN} \ge \delta_E & ; higher\ energy\ nodes \\ if\ R_{SN} \le \delta_E & ; Less\ energy\ nodes \end{cases} \quad (3)$$

From (3),y_i denotes an output of the classifier, δ_E denotes a threshold of residual energy. R_{SN} denotes a residual energy of the sensor nodes. In hidden layer 3, the residual energy of the sensor node is compared with the threshold value. If the residual energy of the sensor node is greater than the threshold value, then the node is said to be a higher energy nodes.

If the residual energy of the sensor node is lesser than the threshold value, then the node is said to be a lesser energy nodes. The output layers display the higher energy and less energy nodes.

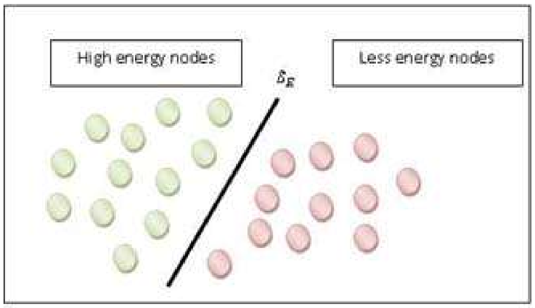

Figure 4 Sensor node classification

As shown in figure 4, sensor node classifications are obtained based on the threshold energy level δ_E. From above figure 4, a green color node represents a higher residual energy whereas a red color node indicates the lesser energy nodes. The node with greater residual energy is chosen for efficient routing in WSN. This assists to expand network lifetime.

3.2 Logit Regression Based Routing in WSN

After selecting the high energy nodes, the regression analysis is performed for finding the nearest neighbor to route the data packet. In the high energy sensor nodes, the source node discovers the nearest neighbor. The source node sends a beacon messages to all the sensor nodes for computing the distance. The distances information's of the sensor nodes are calculated using Time of arrival (ToA) method. Time of arrival is the difference between the beacon message transmitted from the source node and reply message return back to the source node.

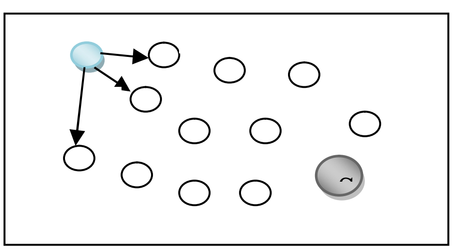

Figure 5 Beacon message distributions

Figure 5 shows the Beacon message distributions to find the nearest neighbor. In figure 5, the blue color node represented as the source node and black colored node indicates the sink node. The source node distributes the beacon message (i.e. m) to all the sensor nodes. The distance between the source node and other sensor nodes are calculated as follows,

$$d = \mathrm{T_B} - \mathrm{T_R} \qquad (4)$$

From (4), d represents a distance among source node and other sensor nodes, $\mathrm{T_B}$ denotes a beacon message transmission time and $\mathrm{T_R}$ denotes a reply message arrival time from the sensor nodes. All the distances information's are collected and perform the regression analysis to find the nearest neighboring node. The proposed EEDNC-LRR technique uses logit regression to analysis the distance information and provides the better output results.

In statistics, the logistic regression is a statistical model to discover the relationship among dependent variable and one or more independent variables. Here, the independent variables are distance information of the sensor nodes and the dependent variable is the outcomes (i.e. neighbor node / distant node) of the regression result.

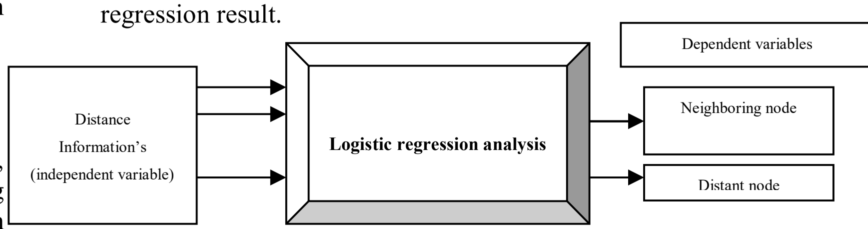

Figure 6 Logistic regression analysis

As shown in figure 6, a Logistic regression analysis is performed between dependent and independent variables. The regressions analysis is performed using the following mathematical equation,

$$P\ (SN) = \frac{1}{1+e^{-(\gamma_i+\gamma_{i+1}*\delta)}} \qquad (5)$$

From (5), $P\ (SN)$ denotes a probability of the dependent variable equaling a "nearest node" or "distant node". γ denotes a regression coefficient and the value of $'i'$ is considered as zero (i.e. 0), δ represents a single explanatory variable. Based on this probability results, the source node makes a decision regarding the nearest node or distant node. By this way, the source node finds the nearest neighboring node to route the data packets. After finding the neighboring node, the source node establishes the links and construct a route path. As a result, the consistent wireless network communication in WSN is provided by means of link quality. If

Journal of Theoretical and Applied Information Technology
15th April 2019. Vol.97. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

any link failure is attained, the source node selects other neighboring node. Higher the link quality, the reliability of data transmission is improved with minimum routing overhead. The algorithmic process of routing is described as follows,

Input: Number of sensor nodes $SN_i = SN_1, SN_2, SN_3 \dots SN_n$, Number of data packets $DP_i = DP_1, DP_2, \dots, DP_n$
Output: Obtain energy efficient routing
Begin
For each SN_i
Measure E_{SN} in the first hidden layer
Calculate R_{SN} in the second hidden layer
Set threshold δ_E in the third hidden layer
if $(\delta_E \geq R_{SN})$ **then**
Classifies higher energy sensor nodes
else
Classifies lesser energy sensor nodes
end if
For all high energy sensor nodes
Source node identifies NN
Compute the distance d
Perform regression analysis $P\ (SN)$
Identify the NN
Construct route from the source node to sink node
Transmits DP_i to sink node through NN
End for
End for
End

Algorithm 1 Energy efficient node classification based routing

The above algorithmic process clearly describes the sensor node classification and routing in WSN. The numbers of sensor nodes are taken as input at the input layer. Then, it fed into the first hidden layer. In this layer, the energy for each sensor nodes is calculated. This result is given to the next hidden layer. Followed by, the remaining energy of each sensor node is computed. Finally, the threshold is set at the third layer to perform the comparison. Based on the comparison result, the higher energy and lesser energy sensor nodes are classified at the output layer. The nodes with high remaining energy are selected for further process resulting prolong the network lifetime. Among the energy efficient sensor nodes, the source node finds the nearest neighboring nodes. Then the source node establishes the links to the nearest neighboring nodes and transmits the data packets to the sink node. By this way, reliable packet delivery is obtained with minimum overhead.

4. SIMULATION SETTINGS

The simulation of the EEDNC-LRR technique and existing methods namely BeeSwarm Approach [1] and DEARER [2] are implemented using NS2.34 simulator. For the simulation purpose, 500 sensor nodes are deployed over the square area of A^2 (1500 m * 1500 m). The Random Waypoint mobility model is exploited for measuring node mobility model. Among the sensor nodes, the energy efficient sensor nodes are selected for routing the number of data packets varied from 10 to 100. The simulation time is set as 300 sec. The DSR protocol is exploited to route the data packets. The simulation parameters and the values are described in table 1.

Table 1 Simulation Parameters

Simulation parameter	**Value**
Simulator	NS2 .34
Network area	1500m * 1500m
Number of sensor nodes	50,100,150,200,250,300,350,400,450,500
Protocol	DSR
Simulation time	300sec
Mobility model	Random Way Point model
Nodes speed	0-20m/s

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Data packets	10,20,30,40,50,60,70,80,90,100
Number of runs	10

The simulation is conducted with the above-said parameters with 10 different instances. The proposed and existing methods are evaluated with different parameters such as energy consumption, network lifetime, reliability of data packet transmission and routing overhead. The simulation results of different parameters are discussed in the next section.

5. RESULTS AND DISCUSSION

The simulation results and discussion of the different parameters such as energy consumption, network lifetime, reliability of data packet transmission and routing overhead with three different methods EEDNC-LRR technique and existing methods namely BeeSwarm Approach [1] and DEARER [2] are described. The selection of the above said parameters is chosen by considering the objective of the proposed EEDNC-LRR technique. The goal of EEDNC-LRR technique is to increase the reliable data packets transmission with minimum energy and routing overhead while performing energy efficient routing in WSN. Based on this goal, the evaluation parameters are selected in the proposed EEDNC-LRR technique. The performance of EEDNC-LRR technique is discussed with the aid of tables and graphical representation.

5.1 Impact of energy consumption

Energy consumption is defined as an amount of energy utilized by the sensor nodes for sensing the environmental conditions in WSN. The formula for energy consumption is measured as follows,

$$E_C = n * E_{SN} \quad (6)$$

From (6), E_C denotes energy consumption, n denotes a number of sensor nodes, E_{SN} denotes energy utilization for single sensor nodes. It is measured in terms of a joule (J).

Sample mathematical calculation for energy consumption

- **Proposed EEDNC-LRR technique:** The total number of sensor nodes are 50, energy utilization for single sensor nodes is 0.65Joule, then the total energy consumption is computed as follows,

$$E_C = 50 * 0.65 = 32.5 = 33\, Joule$$

- **Existing BeeSwarm Approach:** The total number of sensor nodes are 50, energy utilization for single sensor nodes is 0.72 Joule, then the total energy consumption is computed as follows,

$$E_C = 50 * 0.72 = 36\, Joule$$

- **Existing DEARER:** The total number of sensor nodes are 50, energy utilization for single sensor nodes is 0.81 Joule, then the total energy consumption is computed as follows,

$$E_C = 50 * 0.81 = 40.5 = 41\, Joule$$

Table 2 Number of sensor nodes versus Energy consumption

Number of sensor nodes	Energy consumption (Joule)		
	EEDNC-LRR	BeeSwarm Approach	DEARER
50	33	36	41
100	38	42	48
150	39	47	51
200	44	50	56
250	45	53	58
300	48	54	60
350	53	56	63
400	52	60	64
450	54	59	63
500	5	65	7

Journal of Theoretical and Applied Information Technology
15th April 2019. Vol.97. No 7

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

5	0

Table 2 describes the performance results of energy consumption versus a number of sensor nodes. For the experimental consideration, the numbers of sensor nodes are varied from 50 to 500. The energy consumption for each sensor nodes is computed. Ten different runs are carried out with the number of sensor nodes. For each run, the various performance results of energy consumption are obtained. Based on the results obtained in the above tabulation, the energy consumption of EEDNC-LRR technique is minimized when compared to existing methods. The result of using NS2.34 simulators with three different methods are shown in figure 7.

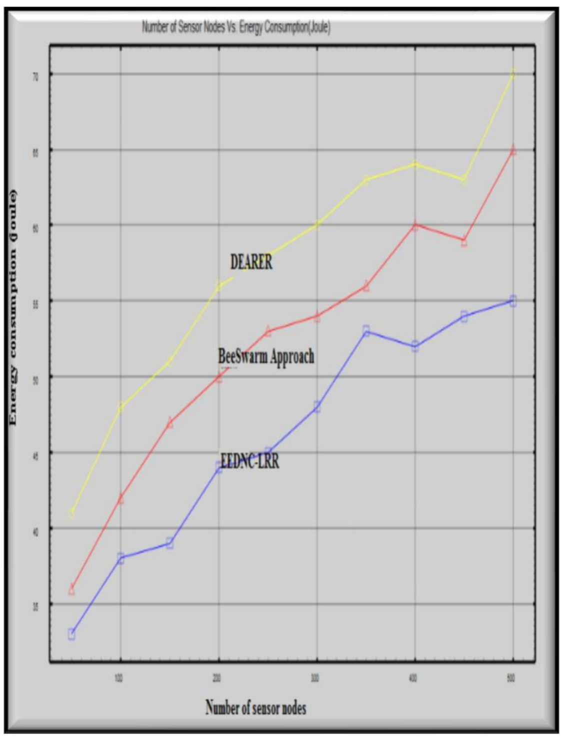

Figure 7 Simulation Results Of Energy Consumption

Figure 7 shows the simulation results of energy consumption versus a number of sensor nodes is illustrated. In figure 7, three different colors of lines such as blue, red, yellow indicate an energy consumption of three different methods namely proposed EEDNC-LRR technique, Existing BeeSwarm Approach [1] and DEARER [2] respectively. The numbers of nodes are taken as input and it shows in the 'x' direction and the corresponding energy consumption results are attained in 'y' direction.

From figure 7, it is clearly observed that the energy consumption is significantly reduced using EEDNC-LRR technique. This is because, the energy efficient deep neural classifier calculates the energy and residual energy of the nodes in the hidden layers. Then the threshold value is set to compare the energy level. If the energy of the node is greater than the threshold value, then the node is classified as higher energy nodes for efficient routing in WSN. If the energy of the node is less than the threshold value, then the node is classified as lesser energy nodes. The lesser energy sensor node contains minimum residual energy and it does not hold the data packets at a longer duration. Therefore, the EEDNC-LRR technique selects the nodes with minimum energy utilization for sensing the data. After computing the energy consumption of three different methods, the comparisons of proposed and existing methods are performed. After the comparison, the energy consumption of EEDNC-LRR technique is minimized by 12% and 20% when compared to existing BeeSwarm Approach [1] and DEARER [2] respectively.

5.2 Impact of network lifetime

Network lifetime is defined as the ratio of a number of higher energy nodes are selected from the total number of sensor nodes for efficient routing. The network lifetime is computed as follows,

$$NL = \frac{\text{Number of higher energy sensor nodes are selected}}{n} * 100 \quad (7)$$

From (7), NL denotes a network lifetime, n denotes a total number of sensor nodes. The network lifetime is evaluated in terms of percentage (%).

Sample mathematical calculation for network lifetime

- **Proposed EEDNC-LRR technique:** Number of high energy sensor nodes selected are 43, the total number of sensor nodes is 50. Then the network lifetime is computed as follows,

$$NL = \frac{43}{50} * 100 = 86\ \%$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- **Existing BeeSwarm Approach:** Number of high energy sensor nodes selected are 37, the total number of sensor nodes is 50. Then the network lifetime is computed as follows,

$$NL = \frac{37}{50} * 100 \ = 74\%$$

- **Existing DEARER:** Number of high energy sensor nodes selected are 33, the total number of sensor nodes is 50. Then the network lifetime is computed as follows,

$$NL = \frac{33}{50} * 100 \ = \ 66\ \%$$

Table 3 Number Of Sensor Nodes Versus Network Lifetime

Number of sensor nodes	Network lifetime (%)		
	EEDNC-LRR	BeeSwarm Approach	DEARER
50	8 6	74	6 6
100	9 3	85	7 8
150	9 1	82	7 5
200	9 4	83	7 6
250	9 6	88	7 7
300	9 3	85	7 5
350	9 5	86	7 9
400	9 7	84	7 8
450	9 5	87	7 7
500	9 6	86	8 1

As shown in table 3, the simulation results of network lifetime based on the number of sensor nodes. The network lifetime is computed based on the selection of higher energy nodes. The above calculation shows that the energy efficient nodes are selected to prolong network lifetime. The simulation results of EEDNC-LRR technique and existing BeeSwarm Approach [1] and DEARER [2] are illustrated in figure 8.

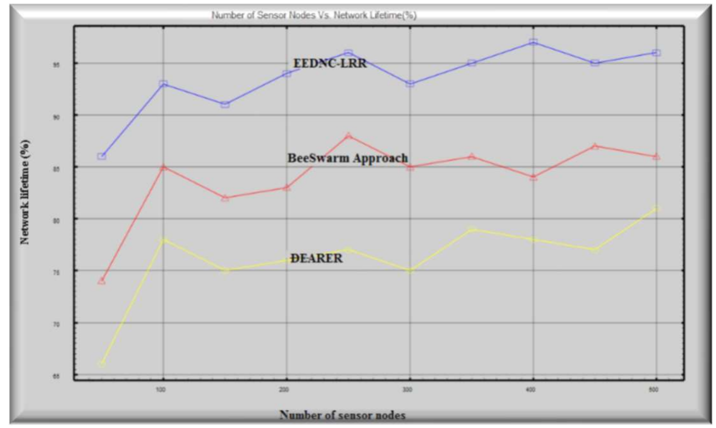

Figure 8 Simulation Results Of Network Lifetime

Figure 8 depicts the simulation results of network lifetime with respect to a number of sensor nodes. As shown in the figure, network lifetimes of three different methods are computed with the energy efficient nodes. The simulation results significantly show that the EEDNC-LRR technique enhances the network lifetime when compared to existing methods. This significant improvement is achieved by selecting the energy efficient nodes among the number of sensor nodes since the high energy nodes are presented until the whole process is completed. It means that sensing, organizing and routing the data packets to the base station. But the lesser energy nodes are not able to perform these kinds of tasks resulting minimizing the duration of the network lifetime. Therefore, the EEDNC-LRR technique uses the energy efficient deep neural classifier for classifying the energy efficient sensor nodes among the number of sensor nodes in WSN. These energy efficient nodes increase the network lifetime.

Totally ten runs are performed to show the efficiency of the EEDNC-LRR technique. Let us consider the 50 sensor nodes, the EEDNC-LRR technique selects the 43 sensor nodes as energy efficient nodes. The other existing BeeSwarm Approach [1] and DEARER[2] selects the energy efficient nodes are 37 and 33 respectively. The existing approach selects only less number of energy efficient nodes hence the network lifetime is minimized. But the proposed EEDNC-LRR technique selects a number of energy efficient nodes to perform routing which results enhance

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the network lifetime. The results show that, EEDNC-LRR technique improves the network lifetime by 12% and 23% when compared to existing BeeSwarm Approach [1] and DEARER[2] respectively.

5.3 Impact of reliability

Reliability is measured in terms of packet delivery ratio which is defined as the ratio of a number of data packet delivered at the sink node to the total number of data packets sent from the source node. It is computed as follows,

$$R = \frac{Number\ of\ DP_r}{Number\ of\ DP_s} * 100 \quad (8)$$

From (8),R denotes reliability, DP_r denotes a data packet received, DP_s represents a data packet sent. The reliability of the data packet delivery is measured in terms of percentage (%).

Sample mathematical calculation for reliability

- ❖ **Proposed EEDNC-LRR technique:** Number of data packets received is 7, the number of data packets sent is 10. Then the reliability is calculated as,

$$R = \frac{7}{10} * 100 = 70\%$$

- ❖ **Existing BeeSwarm Approach:** Number of data packets received is 6, the number of data packets sent is 10. Then the reliability is calculated as,

$$R = \frac{6}{10} * 100 = 60\ \%$$

- ❖ **Existing DEARER:** Number of data packets received is 5, the number of data packets sent is 10. Then the reliability is calculated as,

$$R = \frac{5}{10} * 100 = 50\ \%$$

Table 4 Number Of Data Packets Versus Reliability

Number of Data Packets	Reliability (%)		
	EEDNC-LRR	BeeSwarm Approach	DEARER
10	70	60	50
20	80	70	60
30	87	80	67
40	88	83	75
50	92	86	82
60	93	85	80
70	94	87	81
80	96	91	86
90	94	89	83
100	96	86	80

Table 4 describes reliability in terms of data packet delivery versus a number of data packets. The above table clearly shows that the different delivery rates using three different methods namely EEDNC-LRR technique, BeeSwarm Approach [1], DEARER [2]. The reliability of the data packet delivery is improved in EEDNC-LRR technique than the existing methods. For the experimental purposes, the numbers of data packets are taken from 10 to 100. The simulation results of reliability with three different methods are illustrated in figure 9.

Figure 9 depicts the simulation results of reliability based on a number of data packets. The numbers of data packets are taken for the simulation purposes are varied from 10 to100. From the figure, it is clearly shown that the reliability of the data packet delivery is improved using EEDNC-LRR technique when compared to existing methods. This major improvement is achieved by applying a regression analysis to identify the nearest neighboring node. The nearest neighboring nodes are determined to calculate the distance.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

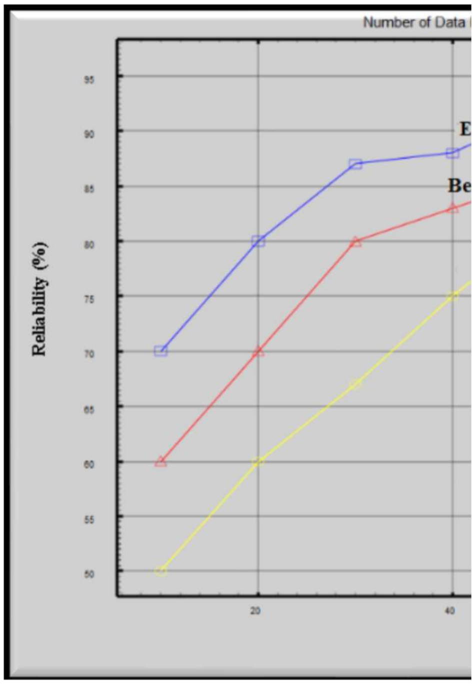

Figure 9 Simulation results of reliability

The source node sends the beacon messages to all the sensor nodes. Followed by, the other sensor nodes sent reply messages back to the source node. The time for beacon message transmission and reception is computed. Based on the time difference, the distances between the nodes are identified. Then these distance information's are used as input of the logit regression. The regression analysis of the input and output variables are performed to find the nearest neighbor node. The node with minimum distances is selected for efficient routing. Through the beacon message distribution, the links between the nodes are established and construct the route path from source to sink node. Along the route path, the source node sends the sensed data packets to the sink node. This helps to improve the data packet delivery. If any link failure occurs in the route path, other nearest neighbor node is selected through the time of arrival method for efficient data packet transmission. Therefore, the reliability is considerably increased by 9% and 21% compared to existing BeeSwarm Approach [1], DEARER [2] respectively.

5.4 Impact of routing overhead

Routing Overhead is measured as the amount of time taken to transmit the data packets from the source node to the sink node through the neighboring nodes. The routing overhead is computed mathematically as follows,

$$Routing\ overhead = Number\ of\ DPs * T(routing\ one\ DP) \quad (9)$$

From equation (9), DPs represents a number of data packets and T denotes a time for routing the data packet. The routing overhead is evaluated in milliseconds (ms).

Sample mathematical calculation for routing overhead

- **Proposed EEDNC-LRR technique:** Number of data packets are 10, time for routing one data packet is 1.1ms. Then the routing overhead is calculated as,

$$Routing\ overhead = 10 * 1.1ms = 11ms$$

- **Existing BeeSwarm Approach:** Number of data packets are 10, time for routing one data packet is 1.3ms. Then the routing overhead is calculated as,

$$Routing\ overhead = 10 * 1.3\ ms = 13ms$$

- **Existing DEARER:** Number of data packets are 10, time for routing one data packet is 1.5ms. Then the routing overhead is calculated as,

$$Routing\ overhead = 10 * 1.5\ ms = 15ms$$

Table 5 Number Of Data Packets Versus Routing Overhead

Number of Data Packets	Routing overhead (ms)		
	EEDNC-LRR	BeeSwarm Approach	DEARER
10	1 1	13	1 5
20	1 4	16	2 0
30	1	21	2

	8		4
40	2 0	26	2 9
50	2 3	28	3 1
60	2 2	26	3 3
70	2 6	29	3 2
80	2 9	31	3 4
90	3 1	32	3 6
100	3 2	34	3 8

The simulation results of routing overhead versus a number of data packets are clearly described in table 5. The table values show that the routing overhead is considerably minimized in proposed EEDNC-LRR technique than the existing BeeSwarm Approach [1], DEARER [2] respectively. The simulation results of the proposed and existing methods with the number of data packets are shown in figure 10.

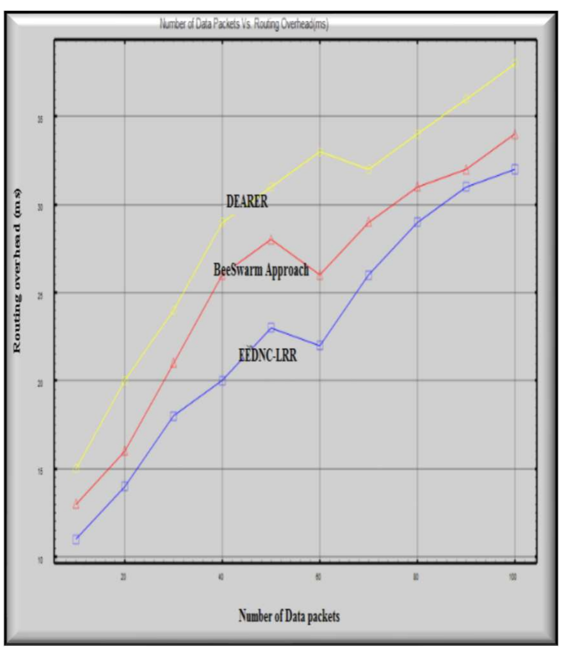

Figure 10 Simulation results of routing overhead

As shown in figure 10, the simulation result of routing overhead with respect to a number of data packets is described. The above figure shows that the numbers of data packets are taken as input for performing the data packet routing from source to sink node. From the figure, the simulation result of routing overhead using EEDNC-LRR technique is minimized when compared to existing methods. This is because, the distance between sensors nodes are calculated to construct the route path among source and sink node through the time of beacon message transmission and arrival. Therefore, the nodes with minimum distance are selected to transmit the data packets. Based on the distance measure, the source node finds the nearest neighboring nodes. The source node sends the route packet through the neighboring nodes for data packet transmission in WSN. This helps to improve data packet transmission with minimum time. Totally ten comparison results of routing overhead are obtained. The result shows that the routing overhead of EEDNC-LRR technique significantly reduced by 12% and 23% when compared to existing BeeSwarm Approach [1], DEARER [2] respectively.

6. FINDINGS

The results of EEDNC-LRR technique is tested with 500 number of sensor nodes with 100 data packets. The Random Way Point model is used as the mobility model and the DSR routing protocol is used validation purpose. By using the simulation settings, the EEDNC-LRR technique proves the performance effectiveness. The proposed EEDNC-LRR technique includes the several advantages compared to similar works previously used to analyze the performance of energy efficient routing in WSN. At first, the basic energy calculation process of this technique is the energy efficient deep neural node classification which determines the RE of nodes after sensing the data packets or information. The node is classified as a higher RE node and lower RE node. The result of energy consumption and routing overhead is reduced by 16% and 18% using EEDNC-LRR technique than the state-of-the-art methods. The technique proposed to construct the energy efficient routing through executing Logit Regression. The source node identifies the nearest neighbor and transmits the data packets to the sink node. Taking into consideration, the proposed EEDNC-LRR technique increases the network lifetime by 18% and reliability by 15% when compared to existing methods.

7. CONCLUSION

A new technique called Energy Efficient Deep Neural Node Classifier based Logit Regressed Routing (EEDNC-LRR) is introduced for enhancing the network lifetime and reliability with minimum energy consumption. In EEDNC-LRR, energy efficient deep neural node classifier takes the number of sensor nodes as input and computes their initial energy and remaining energy level at the different hidden layers. Then the classifier set the threshold value for the node residual energy. Based on the threshold value, the sensor nodes are classified as high energy and low energy. After that, the Logit Regression Analysis is performed with the high energy sensor nodes to find the nearest neighbor. Then, the route is established between the source node and the sink node. Along the route, the data packets are transmitted resulting improve the packet delivery ratio with minimum overhead. The simulation is conducted with different performance metrics such as energy consumption, network lifetime, reliability and routing overhead. The simulation result shows that the EEDNC-LRR technique prolongs network lifetime and improve data packet delivery with minimum energy consumption as well as routing overhead than the state-of-art methods.

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