Bivariate Regression Adaptive Wald's Boost Energy Aware Routing For Wsn With IoT

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ABSTRACT: WSN is a wireless network where the low powered devices known as sensor nodes which are deployed over the network to measure the environmental conditions. IoT is a model that connects WSN and the Internet through a medium depends on wireless Internet technology sensors. However, the large-scale acceptance of WSN for IoT is still facing the major challenges of routing. In order to improve the routing in WSN, an efficient technique called Bivariate Regressed Adaptive Wald's Boost Energy Aware Routing (BRAWBEAR) is introduced. The main aim of BRAWBEAR technique is to improve the data delivery with minimum delay as well as routing overhead. Initially, the energy of the each sensor nodes is measured to improve the energy efficient routing in WSN. The Adaptive Wald's Boost ensemble technique initially comprises the weak learners as a bivariate regression tree with the training samples as sensor nodes. The regression tree analyzes the node energy level with the threshold and categorizes the node into two classes such as higher energy and lesser energy. The Adaptive Wald's Boost ensemble technique combines the weak learner results into make a strong one resulting increases the accurate sensor node classification with minimum error. After that, the route path discovery is carried out with the higher energy nodes and the sensor nodes with lesser energy are removed. The source node finds the neighboring energy efficient node by applying the time of arrival method. Then the route path is established from source to sink node via neighboring nodes. Followed by, the data packets are transmitted along the route path. Finally, the route maintenance is carried out when the link failure occurs by selecting the alternative energy efficient neighboring node to improve the data packet delivery with minimum time. The performance of the proposed BRAWBEAR technique is estimated using the metrics namely, energy consumption, packet delivery ratio, routing overhead, throughput and end to end delay. The comparative results discussion provides the improved performance in terms of minimum routing overhead and higher packet delivery as well as minimum energy consumption than the other well-known routing methods.

Keywords: WSN, IoT, energy aware routing, Adaptive Wald's Boost, bivariate regression tree, time of arrival method

1. Introduction

WSN is a smaller amount of power and scalable network used for IoT applications like home automation, patient monitoring industrial device and so on. IoT scenario normally involves higher reliability of data sent from source to destination sensor node. During the data transmission of packets, a route path from source to destination node identification is essential to attain higher packet delivery ratio.

An Energy-Efficient Optimal Multi-path Routing (EOMR) Protocol was designed in [1] to increase the reliability of data transmission for WSN based IoT application. The designed method failed to obtain lesser overhead in the data transmission. An Improved Stable Election Routing Protocol (I-SEP) was introduced in [2] for Heterogeneous WSN -IoT based routing. The designed protocol enhances the network lifetime but the other QoS parameters were not considered.

A new energy-efficient method depends on fuzzy logic and reinforcement learning was introduced in [3] for enhancing the network lifetime. Though the method reduces the end to end delay, the major routing parameter such as packet delivery ratio was not considered. An energy-aware and secure multi-hop routing (ESMR) protocol was designed in [4] to enhance the performance of routing with lesser energy consumption. However, the ESMR protocol has higher routing overhead.

A Rectangular Rationale Correlated Bayesian (RRCB) technique was developed in [5] to enhance the secure IoT aware data communication with lesser energy utilization. But the performance of throughput was not improved. An energy-efficient and delay-aware routing algorithm was designed in [6] for real-time routing to decrease the energy consumption and minimize the delay. However, the designed routing algorithm failed to transmit the packet to destination through an energy efficient relay node. In [7], a new Neuro-Fuzzy Rule Based Cluster Formation and Routing Protocol were introduced.

A Reliable Cluster-based Energy-aware Routing (RCER) protocol was developed in [8] for heterogeneous WSN, which extend the network lifetime and minimize the routing cost. However, the RCER protocol not efficient to minimize the routing latency. A Neuro-Fuzzy Rule Based Cluster Formation and Routing Protocol were introduced in [9] for performing an efficient routing but accurate energy efficient node identification was not considered.

The centroid routing protocol was introduced in [10] based on the energy parameters for WSN-assisted IoT to enhance the routing facility of the network. But the other Qos routing metrics such as delay, throughput, and overhead was not considered.

1.1 Our contributions

The contributions of the articles are as follows:

- The BRAWBEAR technique is designed for improving the routing performance of IoT interoperable WSNs with minimum delay and routing overhead.
- The Adaptive Wald's Boost technique is applied to find the better energy optimized nodes with the help of bivariate regression tree. On the contrary to existing routing technique, the BRAWBEAR technique performs node classification by applying an Adaptive Wald's Boost technique with a higher density of sensor nodes.
- In route discovery, the BRAWBEAR technique finds the neighboring sensor nodes by distributing the hello messages to all the nodes. The time of arrival method is applied to find the neighboring nodes. Followed by, the route path is established and starts to perform data transmission. This routing technique improves the throughput and reduces the delay of transmission between the nodes.
- Improving the transmission reliability of IoT supporting WSN, the BRAWBEAR technique performs route maintenance.
- Performing a comparative analysis of the proposed technique with the existing methods to analyze its performance with various routing metrics.

1.2 outline of paper

The outline of the paper is arranged into different sections as follows: sections 2 present a detailed analysis of the related works. In Section 3, the proposed BRAWBEAR technique is discussed with its different phases and the architecture considered in the paper. The performance of the proposed technique is evaluated using different metrics in Section 4. Followed by the comparative analysis of proposed and existing scenario is presented. At last, the conclusion of the manuscripts is explained.

2. Related Works

In order to improve the throughput, an Energy and interoperable aware routing technique was introduced in [11]. The method failed to achieve higher delivery ratio while considering the number of data packets. A lightweight synchronization algorithm was designed in [12] for transmitting the data packets towards the sink node. But the algorithm did not select optimal energy efficient sensor nodes for routing.

Forwarding Zone enabled multi objective optimization technique was performed in [13] for power aware routing with lesser delay. The designed technique failed to apply the IoT based dense wireless sensor network. A modified LEACH protocol was developed in [14] for routing the data packets with higher throughput. The designed protocol failed to extend for heterogeneous routing protocols for finding the different results.

A Survivable path routing technique was introduced in [15] with the remaining energy level of the nodes. The technique enhances the delivery ratio but the optimal overhead was not obtained. Multi criteria based cluster head/zone head selection method was developed in [16] for IoT based WSN by considering node energy and network lifetime. The designed method failed to extend for various circumstances in IoT based systems. An anchor-based routing protocol was developed in [17] to obtain better performance in terms of energy consumption. However, the various routing metrics was not considered.

An application-centric information-aware routing (ACIAR) method was introduced in [18] for route discovery and weighted neighbor selection to provide seamless data transfer support for IoT enabled WSN. A Bipartite-Flow Graph Modeling technique was introduced in [19] for effective Fault-Tolerant Routing with lesser energy consumption. But the technique failed to attain the reliability of data delivery. Two energy-efficient models was developed in [20] for WSNs to enhance the better energy efficiency and minimize the delay. However the designed models failed to use several base stations for investigation.

3. Methodology

A Bivariate Regressed Adaptive Wald's Boost Energy Aware Routing (BRAWBEAR) is designed for WSNs with IoT networks. This BRAWBEAR technique is introduced for providing optimal neighboring nodes and path discovery in IoT incorporated application. Neighbor discovery is focused to enhance the communication between devices and energy harvesting of the WSN. The rate and size of sensor data transmitted based on the application supported by IoT. Therefore in this BRAWBEAR technique, neighbor discovery and sensor information transmission are focused to support IoT based applications.

3.1 System model

This section describes the system model of an IoT -WSN. This system model is used to understand that the proposed approach is how to achieve the routing efficiency. In this article, the architecture of WSN-IoT as illustrated in Figure 1. The architecture consists of sensor, sink and internet. The sensor nodes in the WSN are capable of sensing the information from the environment. This information transmission is responsible for integrating communications between the devices. Then the sink node to support energy-efficient sensor nodes is demanded by the IoT applications to meet the user requirements.

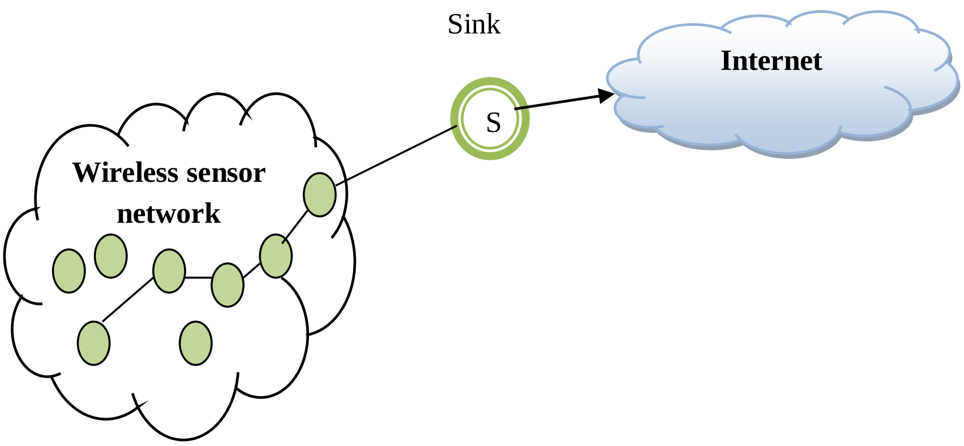

Figure 1 IoT-based WSN

Figure 1 illustrates a circumstances of WSN in IoT with a multiple sensor nodes '$sn_1, sn_2, sn_3, \dots sn_n$', one sink node '$S$' respectively that also acts as the gateway node. Therefore, a number of sensor nodes in WSN connect to the internet through sink node. In this work, an IoT-enabled WSN is designed that uses IoT sensors for routing. Let us consider the WSN is organized in a graphical model '$G(v, d)$' where 'v' indicates the vertices i.e. set of sensor nodes deployed in a WSN within the wireless transmission range 'r' and 'd' represents the links between the sensor nodes in the network. The source node in the WSN transmits the '$dp_1, dp_2, .., dp_m$' to each other through the neighboring nodes $nn_1, nn_2, nn_3, \dots nn_b$ following a specified type of routing in WSN. Based on the above system model, the proposed BRAWBEAR technique is designed and the architecture is shown in figure 2.

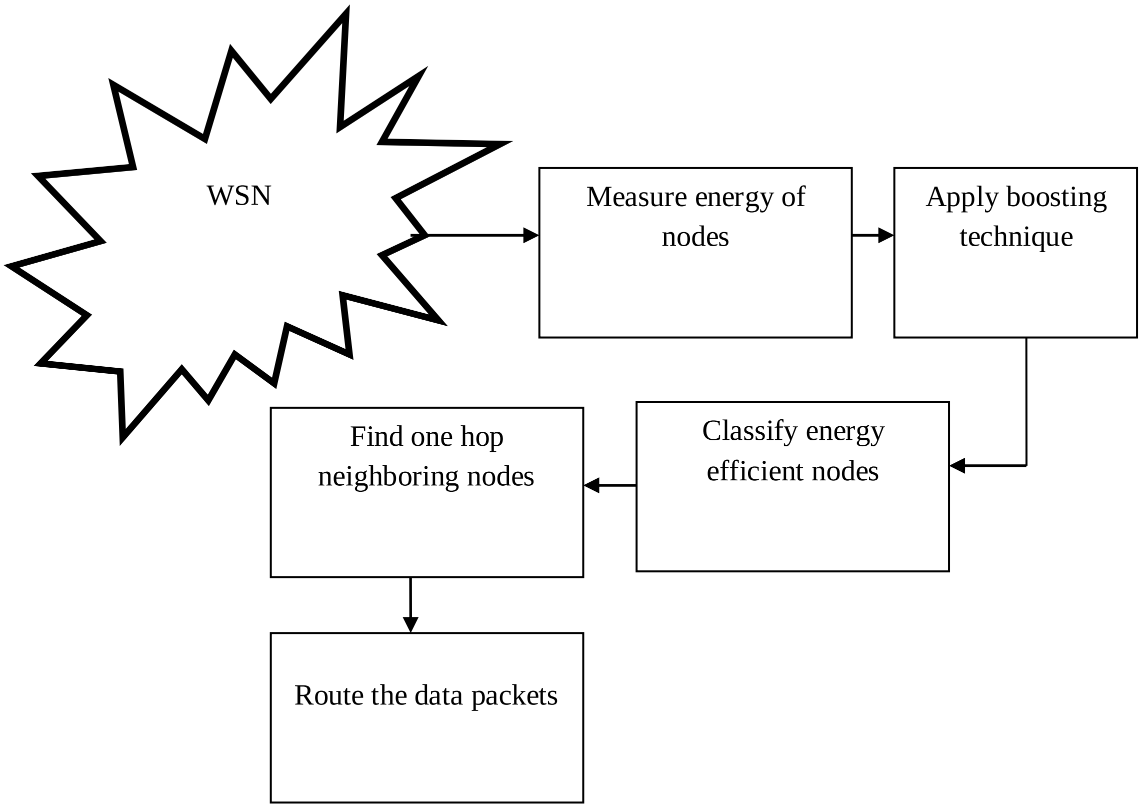

Figure 2 Architecture diagram of BRAWBEAR technique

Figure 2 given above illustrates the architecture of proposed BRAWBEAR technique which includes different processes to identify the energy efficient neighboring sensor nodes in WSN for increasing the routing efficiency with minimum delay. In order to improve the routing in IoT , WSN includes the considerable sensor nodes which have the limited energy. Due to the limited energy of the nodes, the operation of routing efficiency in the network is highly difficult. Therefore the energy efficient nodes are identified to enhance the network lifetime and improve the routing in WSN. Here, the adaptive wald's boost classification technique is applied to classify the higher energy and lesser energy sensor nodes.

Boot classifier is a machine learning methods acts as an ensemble method which is the grouping of simple classifiers (obtained by a weak learner) and provides the better performance than any of the simple classifiers alone. A weak learner is a learning algorithm capable of producing classifiers with probability of error. On the other hand, a strong learner is able to provide the better classification performance with lesser probability. The strategy of boosting, and ensembles of classifiers, is to learn the several weak classifiers and combine them to provide a single strong classifier.

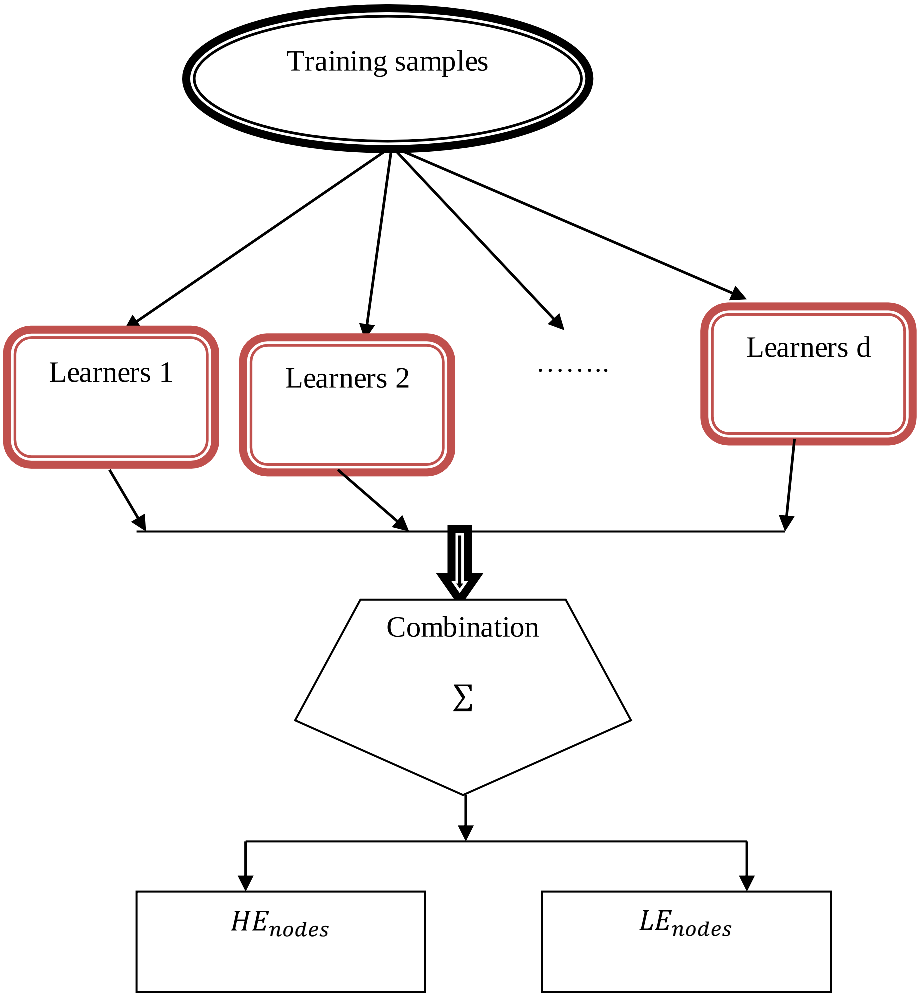

Figure 3 structure of the adaptive Wald boosting algorithm

Figure 3 given above depicts the structure of the adaptive Wald boosting algorithm to increase the classification of the sensor nodes in WSN. The ensemble technique considers the training samples as input i.e. number of sensor nodes $sn_1, sn_2, sn_3, \dots sn_n$. With the training samples, the weak learners are applied to classify the sensor nodes interms of higher energy (HE_{nodes}) or lesser energy nodes (LE_{nodes}). The ensemble technique provides the strong classification results by the combinations of the numerous weak learners. The regression function uses the weak learner to classify the sensor nodes. The regression function is a statistical method used to determine the relationship between two variables with the help of bivariate correlation coefficient. Initially, all the sensor nodes have similar energy level. Due to the sensing and monitoring event of the sensor nodes, the energy level gets degraded. The initial energy level of the node is computed by the means of product of power and time which expressed as follows,

$$\varphi_E = [p_r] * [t_m] \tag{1}$$

Where, φ_E indicates the energy level of the sensor nodes in the WSN, p_r indicates a power and t_m signifies a time. Energy levels of the sensor nodes are determined in the unit of a joule. The energy of the nodes gets degraded due to the sensing and observing the nature of the environment conditions. Therefore, the remaining energy of the sensor nodes is given then following equation,

$$\varphi_{RE} = [tt_E] - [cc_E] \tag{2}$$

Where, φ_{RE} denotes a residual energy of the sensor nodes, tt_E indicates a total energy and cc_E represents an energy consumption of the sensor nodes. Based on the energy level, the nodes are classified using bivariate regression tree classifier. Bivariate regression tree classifier is a machine learning technique which consists of root node, branch node, and leaf node.

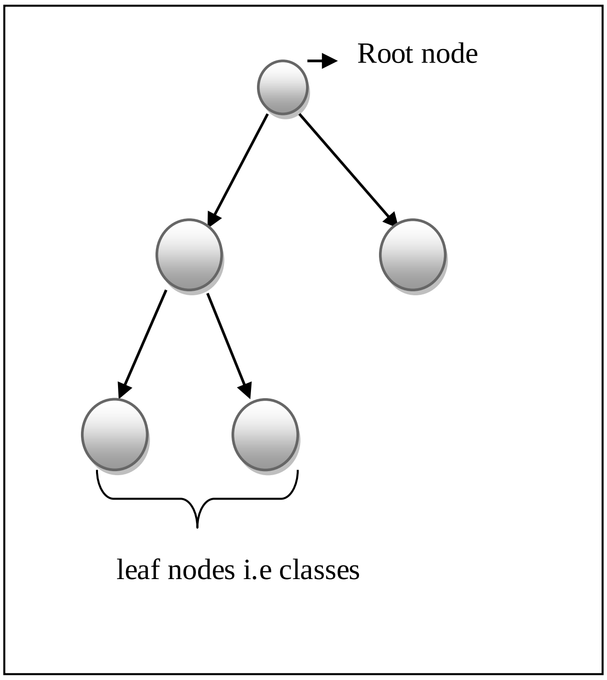

Figure 4 basic structure of the bivariate regression tree

Figure 4 given above depicts bivariate regression tree to categorize the sensor nodes into two classes namely a lesser or higher. For each node in the tree, threshold is set for residual energy in order to classify the sensor nodes.

$$Z = \begin{cases} \varphi_{RE} > \beta \text{ ; } HE_{nodes} \\ otherwise \text{ ; } LE_{nodes} \end{cases} \tag{3}$$

From (3), Z denotes an output of the weak learner, β indicates a threshold for residual energy, HE_{nodes} denotes a higher energy nodes, LE_{nodes} indicates a lesser energy nodes. The output has some training error in the classification results. In order to improve the classification performance and minimize the error, the weak learners are combined into one classifier.

$$H = \sum_{i=1}^{n} Z_i \tag{4}$$

From (4),H indicates an output of the strong classification, Z_i represents the weak classifier results. In order to find the best weak learner, the similar weight is set as given below,

$$H = \sum_{i=1}^{n} Z_i \ \alpha \tag{5}$$

In the above (5),α denotes a weight assigned to the weak learner Z_i. After assigning the weight, the mean square error is computed for finding the accurate classification results of the weak learner by means of Wald's likelihood ratio test. The test is carried out between the sensor nodes and their classes.

$$T_{Ratio} = \log\left[\frac{p_r\langle sn_1, sn_2, sn_3, \dots sn_n|B_1\rangle}{p_r\langle sn_1, sn_2, sn_3, \dots sn_n|B_2\rangle}\right] \tag{6}$$

From (6), T_{Ratio} indicates a Wald's likelihood ratio test, p_r signifies a probability of the sensor nodes $(sn_1, sn_2, sn_3, \ldots sn_n)$ belongs to the class 1 (B_1) or class 2 (B_2). Based on the likelihood ratio test results, the error is computed as given below,

$$R = [Z_{Act} - Z_{Prd}]^2 \tag{7}$$

From the above equations (7), 'R', represent the error with an actual classification results 'Z_{Act}' and the predicted classification output 'Z_{Prd} ' respectively. Followed by, the weight of the weak classifier gets updated according to their weight value. The initial weight gets minimizes when the classifier accurately categorizes the sensor nodes. Otherwise, the weight gets increased. The weak classifier with lesser error is accepted as final best classification results and rejects the other weak classifiers. The final weighted sum of boosting classification results is obtained as follows,

$$H = \sum_{i=1}^{n} Z_i * \alpha_t \tag{8}$$

From (8),H indicates a strong classification results, α_t is an updated weight of weak classifier Z_i . The ensemble classification results are used to find the lesser and higher energy sensor nodes.

3.2 Route discovery

Upon successful classification of sensor nodes, the data packet transmission is carried out with the higher energy sensor nodes. Though the higher energy sensor nodes, initially source and destination is specified and discovers the route path. In order to find the route path, the energy efficient neighboring node is selected. By applying the Time of arrival method, the neighboring node is identified by distributing the hello messages. A neighboring node which has maximum net energy and minimum distance is selected for increasing the routing efficiency.

Initially, the source node 'SN' is specified in the network. The time of arrival method is used to measure the time variation between the hello message transmitted by source node and reply message come back from the another energy efficient nodes in the network. Therefore, the time of hello message arrival is measured as given below,

$$T = T\,[H_{rx}] - T\,[H_{tr}] \tag{9}$$

From (9), T represents a time variation, $T\,[H_{rx}]$ represents a hello message transmission time and $T\,[H_{tr}]$ denotes reply message arrival time. The node which sent reply message with minimum time is considered as neighboring node. In this way, the neighboring nodes are identified.

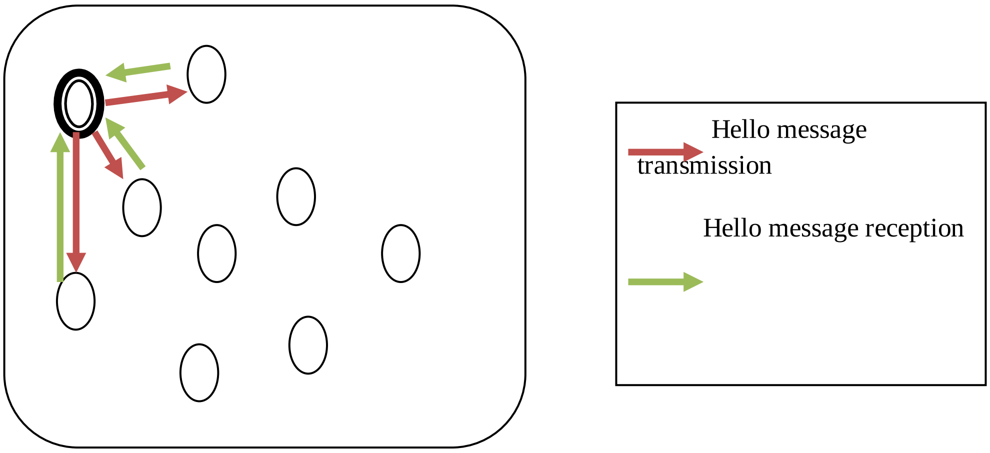

Figure 5 Hello message distributions

Figure 5 given above shows that the hello message distribution to identify the neighboring nodes for data transmission. The source sends the hello message to all the energy efficient nodes. Then the node which has minimum time to send reply back to the source node is said to be a neighboring node. In this way, the neighboring nodes are identified and establish the route between the source and destination. With the selected route, the source node transmits the data packets to destination via energy efficient neighboring nodes. If any link breakages in these networks, it causes higher data packet loss and delay. Therefore, the route maintenance is essential for improving the routing process. Route maintenance is a method to alternative energy efficient nodes towards the destination. This helps to increase the reliability of the data transmission. As a result, Route maintenance is performed only with active routes to improve the network performance.

The algorithmic process of BRAWBEAR technique is described as follow,

Algorithm 1 Bivariate Regressed Adaptive Wald's Boost Energy Aware Routing
Input : number of sensor nodes $sn_1, sn_2, sn_3, \ldots sn_n$, data packets $dp_1, dp_2, dp_3, \ldots . dp_m$ **Output**: Increase the routing efficiency in WSN

Begin
Construct' 'm' weak learners with training samples $sn_1, sn_2, sn_3, \ldots sn_n$
for each sensor node sn_i
Measure residual energy φ_{RE}
If ($\varphi_{RE} > \beta$**) then**
Nodes are classified as higher energy
else
Nodes are classified as less energy
End for
Combine 'm' weak learners $H = \sum_{i=1}^{n} Z_i$
For each Z_i
Initialize the weight 'α'
Compute likelihood ratio test T_{ratio}
Calculate mean square error R
if $arg\,min\ R(Z_i)$ **then**
Accept the weak learner
else
Reject the weak learner
end if
Update the weight 'α_t'
Obtain strong classification results $H = \sum_{i=1}^{n} Z_i \alpha_t$
end for
Source node sends hello message to other nodes
Measure time of arrival $T_{arrival}$
Find neighboring nodes
Establish route between source and destination
Send data packets $dp_1, dp_2, dp_3, \ldots . dp_m$
If any link failure **then**
Select energy efficient node
Send data packets
End if
End

The algorithm given above shows the step by step process of energy efficient routing in WSN. The ensemble learning algorithm is initially applied to classify the lesser and higher energy sensor nodes with the help of weak learners. The bivariate regression tree analyzes the sensor node energy with the threshold to find nodes with lesser energy and higher energy nodes. The ensemble technique combines all the weak learners and identifies the best weak learner with lesser error. After identifying the energy efficient nodes, source node starts to find the neighboring node for data packet transmission. The neighboring node is identified with the help of hello message distribution by the means of time of arrival method. Then the routes are established between the nodes. Finally, in case of any link breakage, the alternative energy efficient neighboring nodes are identified to increase the reliability of data transmission and minimize the delay.

4. Simulation Scenario Setup

In this section, the simulation of proposed BRAWBEAR and two existing methods EOMR [1] I-SEP [2] are carried out using NS2.34 simulator. The various simulation parameters are listed in table I to perform energy efficient routing in WSN.

Table I parameters

Simulation parameters	Values
Network simulation area	1100*1100
Simulation time	300 seconds
Node Mobility model	Random Way Point model
Speed ranges	0-20m/s
Protocol	DSR
Nodes in numbers	{50,100,150,200,250,300,350,400,45,500}
Data packets in numbers	{25,50,75,100,125,150,175,200,225,250}
Total runs	10

The table 1 given above shows the simulation parameters to test the performance of proposed technique against the existing methods [1] [2].

5. Performance Metrics

To measure the performance of our proposed routing algorithm, the following metrics are used and described in this section.

Energy consumption:

Energy is the significant parameters to improve the routing performance in IoT based WSN. In order to perform the routing, energy of the sensor node measurement is essential for improving the network lifetime. An amount of energy consumed by the sensor nodes for delivering the data packets to another sensor node is computed according to the following equation,

$$Con_E = [n] * Con_E\ (Ssn) \qquad (10)$$

From the above equation (10), Con_E signifies the energy consumption of the sensor nodes, 'n' indicates a number of sensor nodes, Ssn indicates the single sensor node. Therefore, the overall energy consumption is measured in the unit of joule (J). Lesser the energy consumption, the method is said to be efficient.

Packet delivery ratio:

Packet delivery ratio is another important metrics to improve the routing efficiency. It is mathematically evaluated as the ratio of data packets successfully received at the sink from the total data packets being transmitted from the source node. The data packet delivery ratio is calculated according to the following equation,

$$DR_{dp} = \frac{[dp_r]}{[dp_s]} * 100 \tag{11}$$

Where, DR_{dp} designates a packet delivery ratio, dp_r data packets received at sink, dp_s indicates data packet being sent. The measurement of delivery ratio is performed in the unit of percentage (%). Higher the delivery ratio, the method is achieved higher routing efficiency.

Routing overhead

The overhead is the major routing performance improvement metrics which is determined in terms of time. The routing overhead is the amount of time taken by the algorithm to transmit the packets from the source to the sink in WSN. The overall routing overhead is calculated with the following equations as expressed below,

$$O_R = [m] * ti\ (route\ one\ dp) \tag{12}$$

From the above (12), m denotes a number of data packets being sent from source, ti denotes a time taken for routing the one data packets (dp). Therefore, the routing overhead is determined in terms of milliseconds (ms).

Throughput

The final routing metric is the throughput which is referred to the ratio of amount of maximum number of packets that a network successfully delivered per unit time. Mathematically, the throughput is calculated by using following expression,

$$T_{put} = \left[\frac{dp\ deliverd\ (bits)}{t\ (\mathrm{sec})}\right] \tag{13}$$

From (13),T_{put} indicates a throughput, $dp\ deliverd$ referred to as data packet delivered in terms of bits, t (sec) indicates a unit time in terms of seconds. Therefore, the throughputs of various methods are calculated interms of bits per seconds (bps).

End to end delay

The final metric considered for analysis of energy aware routing is the end to end delay. It is estimated as the difference between the arrival time of data packets at the sink and data packet transmitting time. The end to end delay is mathematically expressed as given below,

$$D(E2E) = T\{[dp]_{Ar} - [dp]_{Tx}\} \tag{14}$$

From (13), $D(E2E)$ is the end to end delay, T indicates a time, $[dp]_{Ar}$ denotes a data packet arrival, $[dp]_{Tx}$ is the data packet transmitting from source. The delay time of data transmission is measured in milliseconds (ms).

Scenario 1: energy consumption versus number of sensor nodes

In this simulation scenario, the energy consumption of the various senor nodes are determined using (10). This scenario is formulated with the number of sensor nodes in the counts from 50, 100, 150… 500. The ten various results of energy consumption using three different methods are illustrated in table II.

Table II comparison of Energy consumption

Sensor nodes (numbers)	Energy consumption (J)		
	EOMR	I-SEP	BRAWBEAR
50	33	35	28
100	35	40	30
150	38	41	33
200	42	44	36
250	45	48	40
300	48	51	44
350	49	53	46
400	51	54	48
450	54	56	50
500	56	60	53

The scalable performance of the energy consumption of three methods BRAWBEAR and two existing methods EOMR [1] , I-SEP [2] are tested according to the number of sensor nodes in WSN. Table II reports the simulation results of energy consumption by varying the number of sensor nodes. From the experiments conducted in this work, it is proved that the energy consumed by the BRAWBEAR technique is less. From the above statistical results, let us consider the 50 sensor nodes, the energy consumption of BRAWBEAR technique is 28 joule and the energy consumption of EOMR [1] , I-SEP [2] are 33 joule and 35 joule respectively with the similar counts of mobile nodes. Similarly, the nine various statistical results are obtained and the results are illustrated as shown in figure 6.

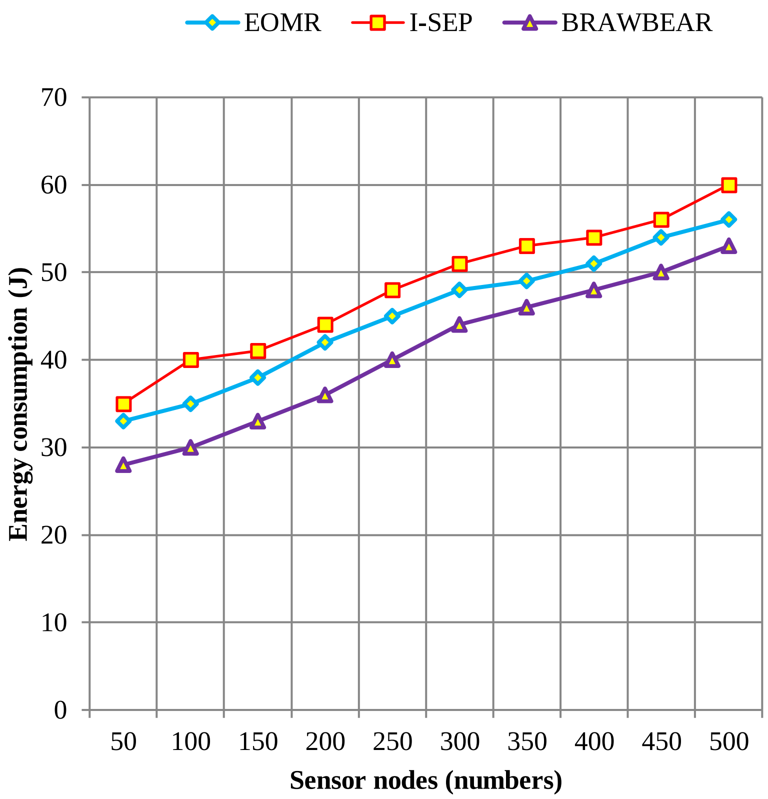

Figure 6 comparison of energy consumption of sensor nodes

Figure 6 given above shows that the comparison of energy consumption with various methods. It is obvious that the energy consumption gets drastically increases as the number of nodes increases, since the increase in the number of nodes consumes more energy. As demonstrates in figure

6, the numbers of sensor nodes are given as input into the horizontal axis of the graph whereas the performance of energy consumption is obtained in the vertical axis. In contrast to other methods, the graph shows that the proposed BRAWBEAR technique is better in terms of energy consumption. The reason is that the proposed BRAWBEAR technique only selects the energy efficient nodes for routing process by applying the ensemble classification technique, which saves the energy and enhances the network lifetime. The average results of BRAWBEAR technique outperforms the other two methods indicates that the energy consumption is found to be minimized by 10% than the EOMR [1] and 16% improved than the I-SEP [2] respectively.

Scenario 2: packet delivery ratio versus number of data packets

In this simulation circumstances, the data packet delivery ratio of three methods are discussed with various counts of data packets from 25, 50, 75… 250. The ten various simulation results of packet delivery ratio of three different methods are depicted in table III.

Table III comparison of packet delivery ratio

Data packets (numbers)	Packet delivery ratio (%)		
	EOMR	**I-SEP**	**BRAWBEAR**
25	84	80	88
50	80	76	86
75	87	83	92
100	84	81	89
125	88	85	93
150	87	83	91
175	89	86	93
200	88	84	92
225	83	80	88
250	88	86	92

As shown in the above the table III, the simulation results of packet delivery ratio with respect to number of data packets are reported. The results indicates that BRAWBEAR technique have higher packet delivery ratio among the other routing methods. This is because the BRAWBEAR technique finds the energy efficient mobile nodes for data delivery. The bivariate regression tree analyzes the sensor nodes energy level with the threshold energy. Based on the regression analysis, the energy efficient senor nodes are identified. The ensemble technique accurately finds the energy efficient sensor nodes to establish the route path for transmitting the data from source to sink node. This process of BRAWBEAR technique reduces the probability of packet loss due to node energy decreases. Compared with EOMR [1] and I-SEP [2], our proposed BRAWBEAR technique considers the residual energy of the node and the optimal effective one hop neighboring nodes is identified to achieve optimal transmission, which ensures the reliability of the network. Therefore, our proposed BRAWBEAR technique outperforms the other two existing routing techniques in packet delivery ratio. The ten various outcomes of the packet delivery ratio according to the data packets as shown in figure 7.

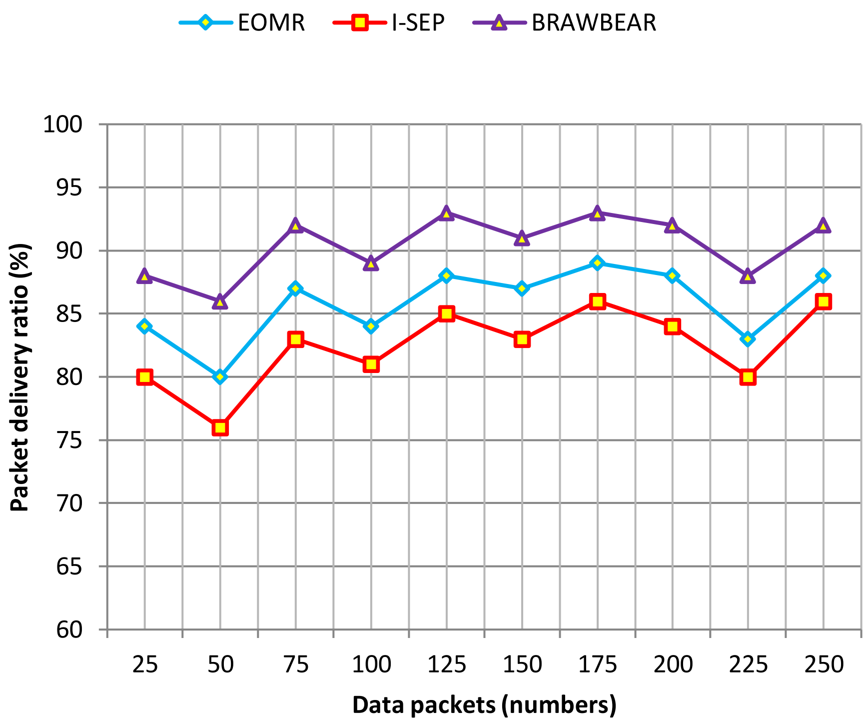

Figure 7 Performances of packet delivery ratio

Figure 7 given above demonstrates the packet delivery ratio under different number of data packets being sent from the source node. Here, the data packets considered for conducting the tests differs in the range of 25 to 250 transmitted over a specified transmission range of the sensor nodes. From the figure it is evident that, BRAWBEAR technique effectively achieves the optimal transmission, which ensures the routing efficiency interms of higher packet delivery.

Scenario 3: routing overhead versus number of data packets

In this subsection, the performance of routing overhead is analyzed with the three methods and the various counts of data packets from 25, 50, 75… 250. In this simulation scenario, the time taken by the sensor nodes distributes the data packets to sink node is identified.

Table IV comparison of routing overhead

Data packets (numbers)	Routing overhead (ms) EOMR	I-SEP	BRAWBEAR
25	23	25	20
50	25	28	23
75	30	33	26
100	35	38	33
125	40	43	38
150	44	48	41
175	46	51	44
200	51	54	48
225	54	56	51
250	55	58	53

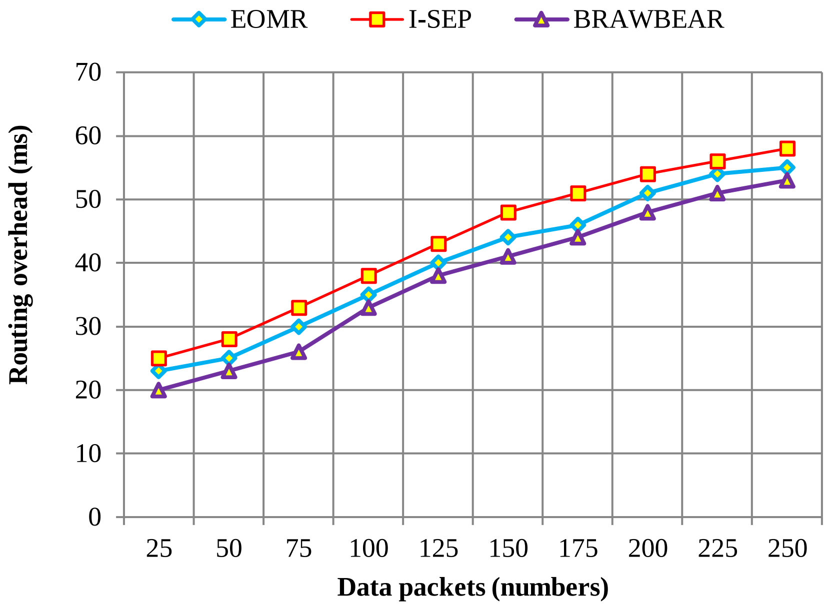

Figure 8 Performances of routing overhead

Table IV and figure 8 shows the performance assessment of routing overhead over different numbers of data packets in the range of 25 to 250 for 10 different simulation runs conducted over a wide area of network 1100m*1100m. From the figure it is evident that, increasing the number of data packets, routing overhead are said to be increased. From the simulations conducted for 25 data packets, the routing overhead is observed $20ms$ using the proposed BRAWBEAR technique, $23ms$ and $25ms$ when applying with the EOMR [1] method and I-SEP [2], method respectively. Among three routing methods, the proposed BRAWBEAR technique minimizes the routing overhead. The reason is that the efficient route path from the source and destination is identified by selecting the energy efficient neighboring nodes. This energy efficient node considerably increases the data packets transmission with lesser overhead. Therefore minimizing the average routing overhead using BRAWBEAR technique by 7% compared to [1] and 14% as compared to [2] respectively.

Scenario 4: throughput versus size of data packets

Throughput of data packet delivery is discussed in terms of various sizes the data packets being sent from the source node. The simulation results of various results of throughput are illustrated in table V.

Table v comparison of routing overhead

Data packet sizes (KB)	Throughput (bps)		
	EOMR	**I-SEP**	**BRAWBEAR**
10	145	134	168
20	240	210	295
30	350	310	412
40	480	415	543
50	540	508	610
60	650	580	722
70	720	670	810
80	827	754	945
90	950	870	1020
100	1120	1050	1245

As exposed in the above table V, the proposed BRAWBEAR achieves higher throughput when compared to conventional routing schemes. This significant development of proposed technique is achieved by an effective communication is takes place between the sensor nodes in a dynamic environment. The time of arrival method is used to find the neighboring nodes for better data dissemination. Let us taken as $10\ KB$ size of the data packet being sent from source node, proposed BRAWBEAR achieves the throughput of $168bps$ whereas the throughputs of other two existing methods are $145bps$ and $134bps$ respectively. Similarly, the remaining runs are carried out and compare the results of proposed technique with the existing methods. The comparison result indicates that the average throughput of data delivery is found to be increased by 14% and 26% than the conventional methods [1] [2].

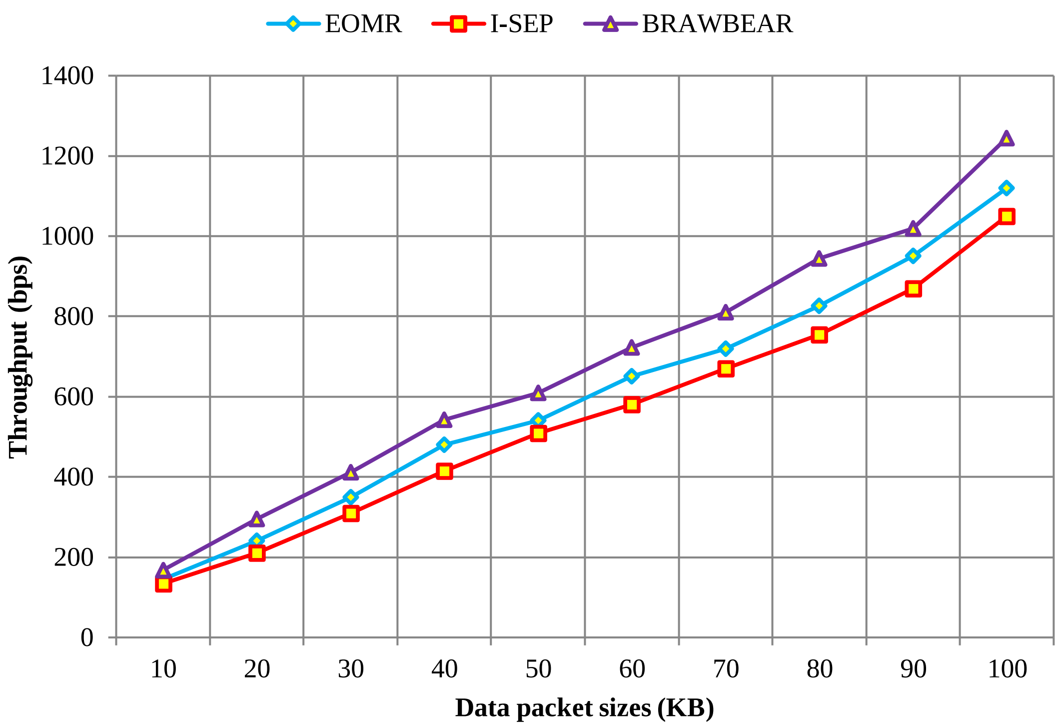

Figure 9 Performances of throughput

Figure 9 displays the impact of throughput along with data packet sizes in the range of 10-100 KB using three methods. While increasing the sizes of the data packets, the throughput of data delivery in IoT enabled WSN is said to be increased for all the three methods. But comparatively, our proposed technique achieved improved performance in terms of higher network throughput.

Scenario 5: End to end delay versus number of data packets

Finally, the simulation results of end to end delay of three routing techniques are analyzed with various counts of data packets. The performance of end to end delay as reported in table VI.

Table VI comparison of End to end delay

Data packets (numbers)	End to end delay (ms) EOMR	I-SEP	BRAWBEAR
25	12	14	10
50	13	15	11
75	15	17	13
100	17	20	15
125	18	21	16
150	21	22	17

175	22	24	20
200	23	25	21
225	26	28	24
250	28	30	25

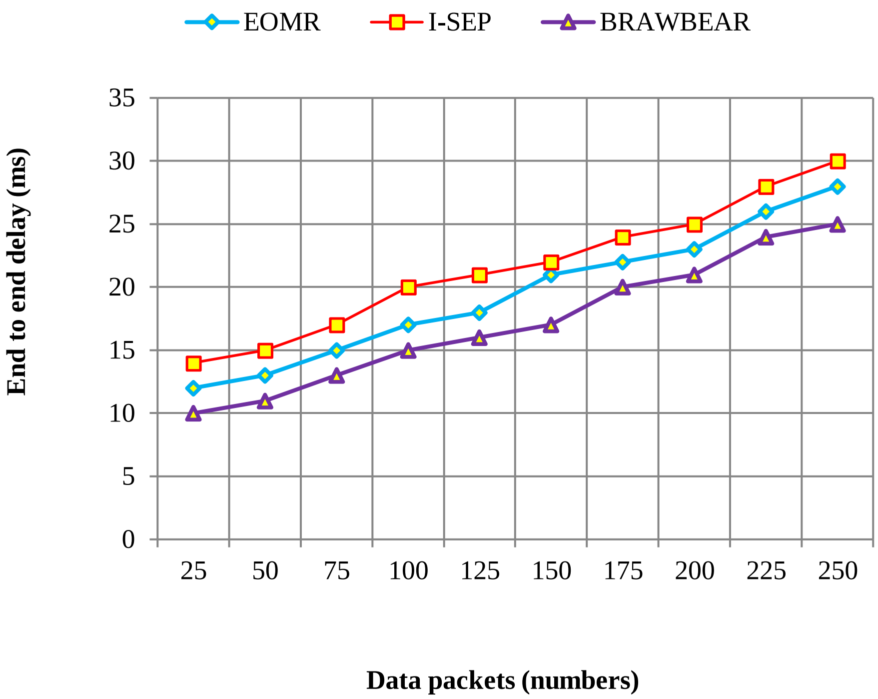

Figure 10 Performances of end to end delay

Figure VI and figure 10 shows the end to end delay with varied number of data packets. The results demonstrate that the delivery delay of our proposed BRAWBEAR is lower than other methods. The main reasons are firstly energy sensor nodes are identified which helps to quickly receive the data packets. Secondly, based on route maintenance, the energy efficient neighboring nodes are identified only forwards the data in case of link failure. This in turn increases the data delivery and minimizes the delay. The average of delay of BRAWBEAR technique is minimized by 12% and 21% than the two conventional routing methods.

5 Conclusion

In this paper, the issue of energy efficient routing is addressed in IoT based WSN. A novel BRAWBEAR technique is introduced to dynamically select nodes with high energy for increasing the packet delivery ratio with minimum delay. Moreover, Adaptive Wald's Boost classification technique is applied to categorize the sensor nodes. The main aim is to improve throughput and minimizes the routing overhead as well as delay. Most of the optimal routing method focuses on the energy consumption part for data routing. As a result, such solutions are non-feasible in dynamic scenarios where the IoT enabled WSN plays a major role in routing. By these innovations, the BRAWBEAR technique performs route path discovery and the route maintenance. The comprehensive simulation is conducted and evaluated with the existing methods. The performance of the proposed technique is evaluated and it has good performance in the energy consumption, packet delivery ratio, throughput and minimizes the routing overhead and end to end delay than the other methods.

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