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Tobit Regressive Resource Optimized Liquid Deep Neural Network Classification for Efficient Data Broadcasting in Wireless Sensor Network

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ABSTRACT
A WSN includes numerous SN that gather sensed data as of sink node and send to BS. Sensor nodes are arranged in a large-scale ad-hoc network. Every SN in these networks is set through wireless data communication device. WSN is employed to handle the data broadcasting services for sensing and transmission. Through data transmission, the sensor nodes consume more energy than data sensing. To address this issue, Tobit Regressive Resource Optimized Liquid Deep Neural Network Classification (TRRO-LDNNC) Method is developed for effective data broadcasting in WSN through minimum energy utilization. TRRO-LDNNC technique includes five layers for carry out resource optimized data broadcast among source as well as destination SN. TRRO-LDNNC collects information packets at input layer from sensor nodes positioned at different locations. Afterward, input layer broadcast the SN to initial hidden layer. In which layer, energy as well as bandwidth utilization of all SN are computed. Then the computed values are broadcasted to second hidden layer. In which layer, Tobit Regression Analysis carried out to examine the energy consumption and bandwidth consumption to perform efficient node classification. The sensor nodes are classified into resource efficient sensor nodes and resource inefficient SN. Resource efficient SN are broadcasted to third hidden layer. In that layer, the neighboring resource efficient sensor nodes with higher signal strength are chosen for data transmission. By this way, data packets are transmitted to BS in WSN in output layer. Experimental assessment is performed on various factors with number of data packets and SN.

Keywords: WSN, Data Broadcasting, IoT, Tobit Regression Analysis, Signal Strength

1. Introduction

WSNs are self-configured as well as infrastructure-minimum wireless networks that examine network conditions to communicate information from sink node to BS. WSNs have vital technology in IoT for enabling seamless incorporation of sensing, communication, computational capabilities. WSNs include number of immobile and homogeneous wireless sensors in a particular manner. WSN is an essential one in diverse applications , where enormous number of sensor tools are deployed in observing area. WSN provides efficient data communication with the help of number of SN in network.

WSNs effectively handle wider network through obtainable resources. So, energy efficiency is significant for enhancing network life span through data broadcast to sink node. Energy management is a major issue in WSN. Wireless communication provides the virtual connection between sensor nodes and the base station without physical cables. BS served as the entrance points in wireless network. However, resource optimized information transmission was not achieved. Due to this problem, the proposed TRRO-LDNNC Method is introduced to obtain resource optimized data transmission.

FFO-WSN has designed in [1] to identify the routing path. FFO-WSN increased network lifetime and data transmission efficiency. Though the network lifetime has improved, the computational cost has not minimized. An adaptive sampling strategy has introduced in [2] depending on spatio-temporal correlation among sensor values. The designed strategy increased energy saving in cluster-based network. But, the delay has not minimized.

Intelligent energy-effective data routing scheme has presented [3] for WSNs with MS to minimize energy utilization for increasing network lifetime. But, delay has not reduced by designed scheme. MIHFO system has developed in [4] for efficient clustering. Cluster head has selected depending on residual energy and node centrality. But, the energy consumption has not minimized by MIHFO system.

FOAUC-SARP framework has introduced in [5] for addressing the energy balancing as well as routing demands in diverse WSNs. Error vector magnitude through hierarchical modulation has introduced [6] to adjust modulation scheme for increasing spectral effectiveness. Though the efficiency has improved, network lifetime has not improved. Hybrid WSN-Long term evolution aided architecture has designed in [7] for increasing the lifetime with quality of service. However, energy utilization has not minimized.
Traffic-aware, cluster-basisof, and energy-efficient routing protocol has designed [8] to enhance the data delivery. Though the network lifetime has improved, the computational complexity has not reduced by designed protocol. An innovative model has designed in [9] for identifying the cluster head position in a WSN. However, the packet delivery ratio has not improved. HMNCS has introduced in [10] with cluster head selection. However, computational cost has not minimized.
Energy-effective clustering and routing method depend on COA has designed in [11] to enhance WSN performance. Though delay has reduced, the computational cost has not minimized. Accelerated Particle Swarm Optimization (APSO) algorithm has designed in [12] with high throughput and network lifetime. Stochastic Cluster Head Selection Model (SCHSM) has designed in [13] with minimum distance. However, the network lifetime has not improved by SCHSM. MFOA-EACO has introduced in [14] with minimum energy utilization. But, energy utilization level has not minimized.
The problems recognized are superior energy consumption, higher computational cost, higher computational overhead, lesser throughput and so on. In order to address these issues, Tobit Regressive Resource Optimized Liquid Deep Neural Network Classification is developed.
Major contribution of TRRO-LDNNC method given as:

- TRRO-LDNNC Method is to perform efficient data broadcasting in WSN. TRRO-LDNNC method comprised input layer, three hidden layers as well as single output layer for resource optimized data broadcast among source and destination SN.
- TRRO-LDNNC Method gathers the data packets from sensor nodes. Tobit Regression Analysis determines the energy consumption and bandwidth consumption for efficient node classification. The sensor nodes are categorized into resource effective SN and resource ineffecive SN.
- Neighboring resource efficient sensor nodes with higher signal strength are chosen through nearest neighbor search in TRRO-LDNNC Method for effective data broadcast in WSN. This in turn, data packets are broadcasted to BS in WSN.
- Result analysis of TRRO-LDNNC Method is performed through dissimilar parameters.

This paper outline is given below. Section 2 provides research literature review. Section 3 explains TRRO-LDNNC Method for carry out effective data broadcasting in WSN. Simulation setting explanation given in Section 4. Outcomes as well as analysis of experiment are given in Sections 5. Conclusion are provided in Section 6.

2. Literature Review

Energy-efficient routing has basic challenge in WSNs. FFO-WSN [1], adaptive sampling strategy [2], and intelligent energy-efficient data routing scheme [3] have developed to enhance the energy efficiency. Optimization methods such as MIHFO [4] and FOAUC-SARP [5] have designed to perform clustering and routing processes. To enhance the data transmission efficiency, the error vector magnitude with hierarchical modulation [6] and Long term evolution assisted architecture [7] have employed.
For improving the data delivery, traffic-aware, cluster-based, energy-effective routing protocol [8] and an innovative model [9] have introduced. To perform cluster head selection and optimization, HMNCS [10] and energy-efficient clustering and routing technique [11], APSO [12], SCHSM [13] and MFOA-EACO [14] have designed. However, energy utilization was not minimized.
In WSN, SN are used to identify, examine and broadcast collected data. T2FHHO has introduced in [15] for selecting best path as of source to destination node. MZ-SEP and MLZ-SEP have introduced in [16] with initialization and network nodes depending on diverse parameter.
CAC-IACA has designed in [17] for finding the best route. IT2FUSS method has introduced in [18] to address the model uncertainties. A systematic end-to-end design has designed in [19] for cluster based WSNs. An efficient routing protocol has introduced in [20] to enhance the scalability. A hybrid evolutionary approach has introduced in [21] to eliminate the congestion in WSN for increasing network performance.
Sequential Convex Approximation (SCA) has introduced in [22] with high throughput for efficient data distribution. But, the computational cost has not reduced by SCA. ML-EOA has introduced in [23] for addressing energy consumption issues. An innovative hybrid methodology has designed in [24] for increasing the localization accuracy. Though accuracy level has improved, time consumption has not reduced by designed methodology. Energy efficient scalable routing algorithm has introduced in [25] through hierarchical agglomerative clustering with energy efficiency. The clustering routing protocol has introduced in [26] to

recognize best path through high energy. Though the efficiency level has improved, the computational cost has not reduced by clustering routing protocol.
EcoWatch has designed in [27] for energy and bandwidth limitations in WSN. However, the complexity level has not reduced by EcoWatch. LEO have designed in [28] for energy-effective routing in WSNs. LEO has used to identify the routes with minimum energy consumption and higher transmission reliability. Though reliability level has improved, time complexity has not reduced by LEO. A routing algorithm has introduced in [29] for energy minimization through optimization strategy in WSN. Calinski Harabasz approach has introduced in [30] for identifying optimum number of clusters. Though the network lifetime has improved, computational cost has not minimized.

3. Methodology

WSN contains number of SN through sensing as well as computing abilities. SN are used for sensing as well as observing the physical metrics and transmit collected information in wireless manner to central BS. WSN use numerous sensors to improve the system dependability. The environment comprised the sensor nodes, sink node and base station. SN are positioned for sensing, monitoring and broadcasting collected information wirelessly to BS. During data communication, SN broadcast the data packets to sink node.

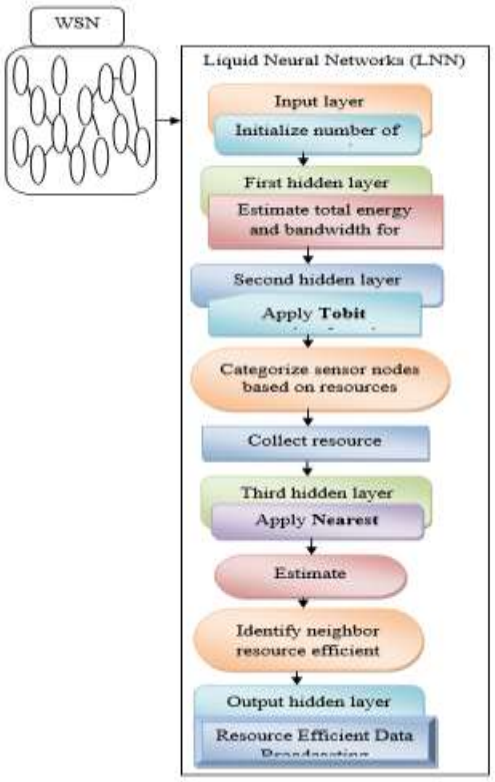

Figure 1: Architecture of Data Communication in Wireless Network

Figure 1 depicts structural design diagram of data communication in wireless network in [31]. WSN is to examine scheme, environmental conditions. SN are employed to handle and observe environment in exact region. They are associated with BS which performs as processing unit in WSN. BS in WSN scheme is associated to Internet to distribute information.
For energy-aware data communication, DL is developed in wireless network to examine sensor tools resource as well as connectivity status for enhancing communication. For achieving the energy-efficient data broadcasting in WSNs, the Tobit Regressive Resource Optimized Liquid Deep Neural Network Classification (TRRO-LDNNC) Method is developed is to carry out effective data broadcasting in WSN.
The architectural diagram of the TRRO-LDNNC Method is illustrated in Figure 2.

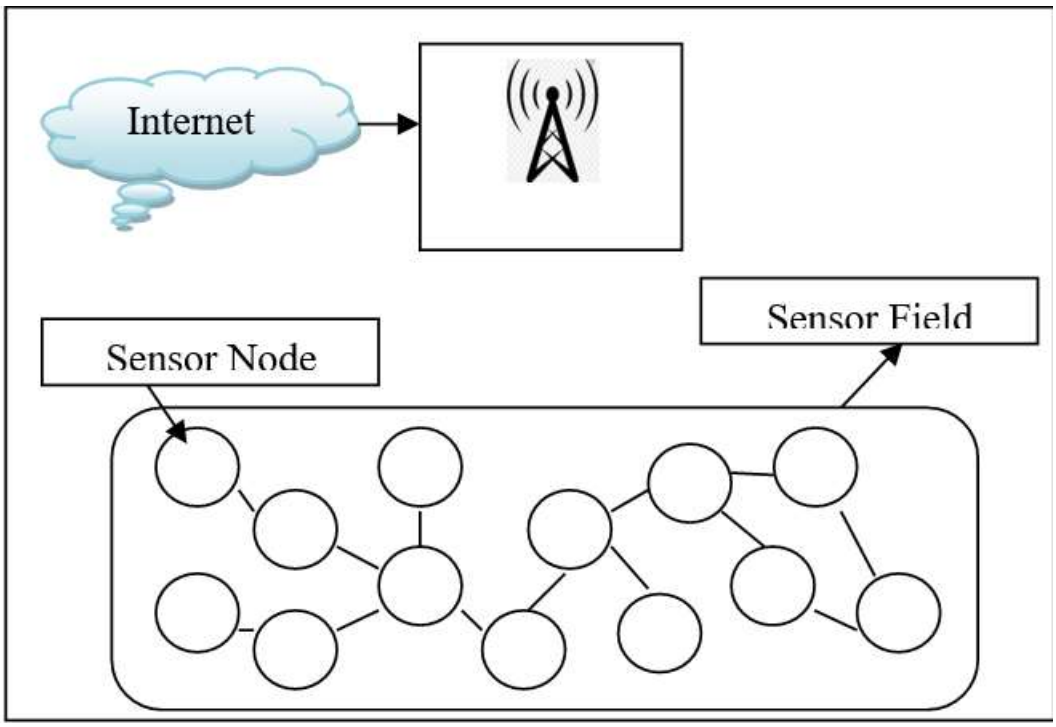

Figure 2 Architecture Diagram of TRRO-LDNNC Method

The proposed TRRO-LDNNC Method architecture diagram is described in Figure 2. It is designed with Tobit Regression and LNN. LNN includes several layers. At first, number of SN is initialized as input in input layer. After that, energy of SN is predefined. Then, the data transmission is performed in hidden layer 2 for computing the resource availability of sensor nodes through performing the Tobit Regression analysis. After that, node classification is performed based on the resource availability. In hidden layer 3, Manhattan Distance is employed to find the nearest neighbor node search with minimal distance. With the help of nearest neighbor search, the data broadcasting is performed in WSN. As a result, resource effective SN are obtained in output layer for carry out efficient information broadcast from the source to the destination node.

3.1 Tobit Regressive Resource Optimized Liquid Deep Neural Network Classification

LNNs are kind of NN to process the data packets and adapt to new inputs over time. LNN is a type of recurrent neural networks in dynamic network of neurons to manage the chronological information. The advantages of LNNs are less computational resources with less model complexity. LNN has synaptic weights that adjust themselves based on incoming data packets.

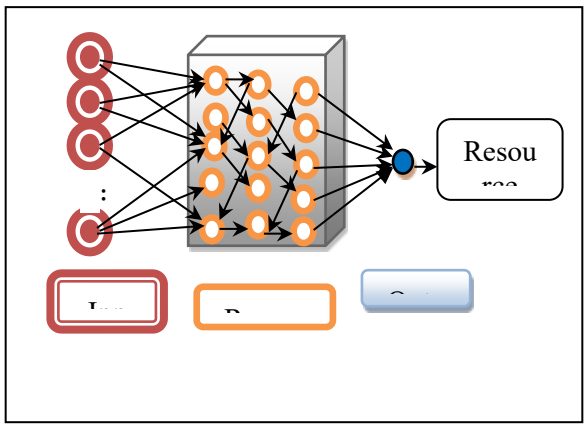

Figure 3 Structure of LNN

Figure 3 illustrates the structure of LNN. LNNs are inspired by the fluid-like behavior of liquids, striving to follow this adaptable nature inside computational systems. In Contrasts to CNNs, LNNs incorporate dynamic connectivity. This approach enables information to flow and interact in a fluid manner, continuously changing manner. The dynamic nature of LNNs permits adapting seamlessly to altering data distributions, making them

particularly effective for tasks that involve non-stationary data. Their fluid-like behavior enables them to self-adjust and filter out immaterial information, thereby improving their generalization capabilities.
The proposed LNN comprised input layer, liquid layer and output layer. Every layer comprised the spiking neurons. LNNs are the ability to adjust the connections between neurons during the learning process. This dynamic adjustment allows the network to change patterns and enables it to capture more complex relationships between neurons, which improve the performance of flexibility and long-term learning. In LNN, neurons are interconnected for continuous and dynamic interaction effectively. At first, the input layer collects the sensor nodes with resource availability. The input layer transmits the information into liquid layer with help of neurons. The liquid layer performs the majority of computation process. The liquid layer comprised the network of interconnected neurons to process the input data in a dynamic manner. The liquid layer is highly flexible with the continuous information flow. The key objective of the liquid layer is to convert the input data into resource resource-optimized one. Finally, the output layer is used for making the final decision. The proposed LNNs employ liquid activation functions that are designed in output layer to simulate behavior of liquids, allowing the network to model continuous processes more effectively. These activation functions enable smooth transitions between more complex patterns.

Initially, input layer takes all sensor nodes. These sensor nodes devices have same energy levels. Also, the input layer sends to initial hidden layer. Total energy of SN is computed as,

$$Energy_{Total}\ (SN_i) = Energy_{Transmit} + Energy_{Process} + Energy_{Standby} \quad (1)$$

Where, '$Energy_{Total}(SN_i)$' represent total energy of ith SN. '$Energy_{Transmit}$' denotes energy dissipated through data broadcast. '$Energy_{Process}$' symbolizes energy dissipated through processing tasks. '$Energy_{Standby}$' represent the energy consumption in standby mode. It is formulated as,

$$Energy_{Transmit} = \left(Energy_{el(Transmit)} * K\right) + \left(Energy_{amp} * K_{Transmit} * D^2\right) \quad (2)$$

Where, '$Energy_{TX}$' represents energy utilized by SN. '$K_{Transmit}$' symbolize the data packet size transmitted. '$Energy_{el(Transmit)}$' represents the energy consumed during single bit data transmission. 'D' denotes distance among SN and BS. Energy consumed computed through multiplying the device power consumption by time consumed for processing the tasks. It is calculated as,

$$Energy_{Process} = \left(Power_{(SN_i)} * Time\right) \quad (3)$$

Where, '$Energy_{Process}$' symbolizes the energy dissipated through processing, $Power_{(SN_i)}$ refers to power utilization .'$Time$' symbolizes period of processing tasks. Standby energy utilization of sensor node computes power usage when tool not carried out tasks however powered on. The standby function maintained the important functions such as maintaining display on standby, etc. The standby energy consumption is formulated as,

$$Energy_{Standby} = Power_{(standby)} * Time_{(standby)} \quad (4)$$

Where, '$Energy_{Standby}$' indicates energy dissipated through standby mode. '$Power_{(stand)}$' denotes the power consumption of sensor node measured in terms of watts (W). '$Time_{(stand)}$' symbolizes the duration of standby mode calculated in seconds (s).
Bandwidth of SN refers to amount of information sent over network in exacting time period. The bandwidth is measured in bps, kbps, Mbps, or Gbps. It is expressed as,

$$BW(SN_i) = \left[\frac{D}{Time(s)}\right] \quad (5)$$

Where, '$BW(SN_i)$' indicates bandwidth of SN. 'D' represents amount of data transmitted over network. Tobit Regression is statistical technique which aids to find out linear association among resources of sensor node.

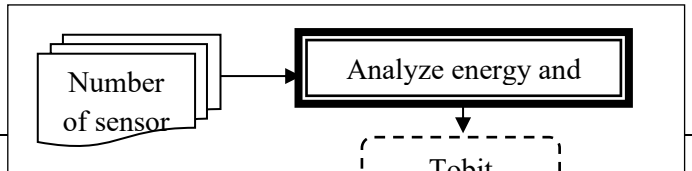

Figure 4 Tobit Regressive Resource Optimization

Figure 4 portrays, the hidden layer 2 performed into Tobit regressive resource optimization. Regression function examines resource availability of SN. Tobit Regressive resource optimization is the model where only resources availability is used to address the constraints. In this model, censoring function is employed to energy and bandwidth availability of sensor node. The fundamental equation of tobit regressive resource optimization is formulated as,

$$R_i' = SN_i\alpha + \epsilon_i \quad (6)$$

Where, 'R_i'' symbolizes the resource availability like energy and bandwidth. In this work, we are intended in the distribution of 'q' given that 'q' is greater than threshold for training sensor node 'SN_i', with 'ϵ_i' corresponding to the 'N' value lying between '0' and 'σ^2'. It finds the connection between the non-negative dependent variable and negative independent variable. It is formulated as,

$$R_i = \begin{cases} RED\ if\ R' > Threshold \\ REID\ if\ R' \leq Threshold \end{cases} \quad (7)$$

Where, the resource availability of sensor node is determined. In Tobit regressive resource optimization model, the sensor nodes are censored or discarded. The function gives output ranges as of 0 to 1. Tobit regression analysis attained similarity values superior than threshold for recognizing RED. When resemblance values are lesser than threshold, radial kernel is used to recognize mobile devices which are not resource-effective.

Algorithm 1: Tobit Regressive Resource Optimization
Input : Number of Sensor Nodes $SN_1, SN_2, SN_3 \ldots, SN_n$ **Output** :Select resource efficient devices
Begin **Step 1: For each** device 'SN_i' **Step 2**: Compute energy '$E_T\ (SN_i)$' **Step 3**: Compute bandwidth '$BW\ (SN_i)$' **Step 4: End for** **Step 5:** Analyze the resources of sensor nodes **Step 6: if** ($R_i > Threshold$) **then** **Step 7**: Node is said to resource efficient for communication **Step 8**: **else** **Step 9**: Node is said to not resource inefficient for communication **Step 10: End if** **End**

Algorithm 1 describes the Tobit Regressive Resource Optimization for identifying resource efficient sensor node to improve data communication performance through lesser delay. Energy and bandwidth are calculated for each sensor node. After that, the tobit regression function analyzes the resource availability. The tobit regression function output better than threshold is employed to discover resource effective SN. Or else, sensor node is resource inefficient sensor node for data communication. After that, resource effective sensor node is broadcasted to next layer for effective data broadcasting. For performing efficient data transmission, the Nearest Neighbor Node Search is performed in hidden layer 3 of proposed TRRO-LDNNC Method. The neighbor node search process is used to identify the resource efficient sensor node with minimal distance. The neighboring node is identified with help of Manhattan Distance. Manhattan distance is employed to determine distance among two resource efficient SN in WSNs. Mathematical formula for estimating the Manhattan distance between two resource efficient sensor nodes '$MH(RESN_1, RESN_2)$' is attained as,

$$MH_{(RESN_1, RESN_2)} = |RESN_1 - RESN_2| \quad (8)$$

Where, '$MH_{(RESN_1,RESN_2)}$' denotes the integer between two sensor nodes. Then, the gradient descent function '$f(x)$' is used for finding the neighboring node with minimal distance. It is formulated as,

$$f(x) = arg\ min\ [MH_{(RESN_1,RESN_2)}] \quad (9)$$

Where, '$arg\ min$' represent argument of the minimum function. From that, the high resource efficient neighboring node with minimal distance is identified. After that, the data packets from high resource efficient sensor nodes are forwarded to the neighboring resource efficient sensor node with minimal distance. The process gets iterated till it reaches base station. Finally, the data broadcasting results are transmitted to the output layer. Consequently, information packets are sent to destination during resource efficient SN with higher throughput with minimized end-to-end delay.

4. Simulation Settings

TRRO-LDNNC Method and conventional methods are FFO-WSN [1] and adaptive sampling strategy [2] are implemented in NS3 network simulator. Random waypoint model is employed as mobility model. DSR protocol is utilized in a simulation scenario in energy-efficient data broadcast in WSN. DSR is on-demand routing protocol and source-routing method for WSN that permits nodes to determine and preserve paths to other nodes without pre-existing infrastructure. DSR operates with two main procedures. In route discovery, source node determines path to destination. Route maintenance discovers as well as recuperates from link failures. DSR is used for resource-efficient SN to reduce network overhead and preserve energy by avoiding periodic routing advertisements. The simulation is carried out in 300 seconds. Speed of SN is diverse in range of 0 to 20 m/s.

Table 1 Simulation Parameters

Simulation parameter	Value
Simulator	NS3
Number of sensor nodes	50, 100, 150, 200, 250, 300, 350,400,500
Network area	1100m * 1100m
Simulation time	300s
Mobility model	Random Way Point
Routing protocol	Dynamic Source Routing (DSR)
Sensor nodes speed	0-20m/s.
Data packets	100,200,300,400,500,600,700,800,900,1000
Number of runs	10

5. Performance Analysis

Simulation analysis of TRRO-LDNNC technique alongside FFO-WSN [1] and adaptive sampling strategy [2] are compared through various evaluation metrics. Result of diverse parameters is examined through tabular as well as graphical illustrations.

5.1 Energy Consumption

The energy consumption of sensor nodes through data distribution is defined as amount of energy consumed for efficient data transmission and number of SN. It is formulated as,

$$Energy_{Cons} = Energy_{Cons}(SN) * \sum_{i=1}^{n} SN_i \quad (10)$$

Where, 'E_{Cons}' denotes energy consumption. 'n' symbolizes number of SN. '$E_{Cons}(SN)$' represent amount of energy utilized by single SN. It is calculated in joule (J). Table 2 illustrates performance study on E_{Cons}.

Table 2 Tabulation on E_{Cons}

Number of sensor nodes (Number)	E_{Cons} (J)		
	FFO-WSN	Adaptive sampling strategy	Proposed TRRO-LDNNC Method
50	22	28	15
100	25	32	18
150	28	35	20
200	31	38	23
250	35	40	26
300	38	42	29
350	41	45	32
400	44	48	36
450	48	50	39
500	52	53	43

The energy consumption measurement is determined in table 2 on the number of data packets for three methods such as FFO-WSN [1] and adaptive sampling strategy [2], and proposed TRRO-LDNNC Method. The simulation of energy consumption parameter is carried out with the comparative analysis between the proposed TRRO-LDNNC Method and two conventional methods. The above table 2 illustrates that E_{Cons} measurement of TRRO-LDNNC Method is lesser than the two conventional techniques. The graph representation of energy consumption is depicted in figure 5.

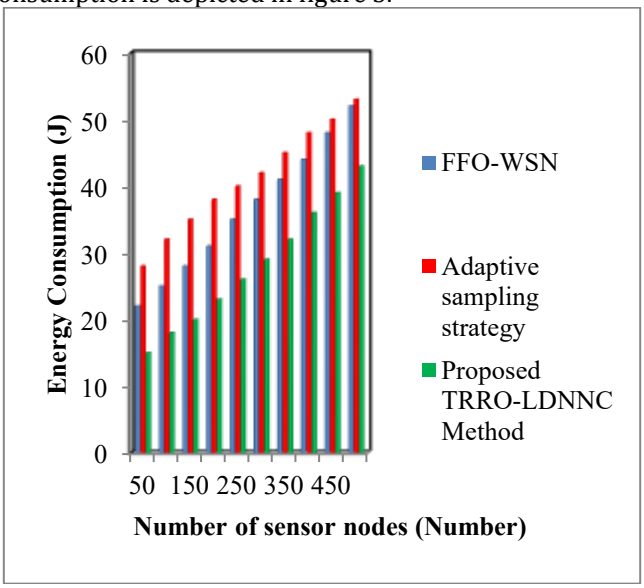

Figure 5 Performance Analysis based on Energy Consumption

According to dissimilar number of SN, finding outcomes for energy consumption of three dissimilar methods are shown in figure 5. Result is obtained through making comparative analysis between the proposed TRRO-LDNNC Method and two conventional techniques. Proposed TRRO-LDNNC Method efficiently minimizes the energy consumption when compared to other two conventional techniques. To do this, Tobit Regression Analysis used to examine the energy consumption and bandwidth consumption to perform efficient node classification. The neighboring resource efficient sensor nodes with higher signal strength are chosen for information transmission. This in turn aids to minimize the E_{Cons}. Thus, energy consumption of the proposed TRRO-LDNNC Method is efficiently reduced by 24%, and 33% than the [1] , [2].

5.2 Packet Delivery Ratio

It is ratio of total number of data packets effectively received at base station to number of data packets transmitted from source node. It is calculated as

$$PDT = \left(\frac{Dp\ received}{Dp\ sent}\right) * 100 \quad (11)$$

Where, '*PDT*' symbolizes the packet delivery ratio. *PDT* is in percentage (%). Table 3 illustrates result analysis on *PDT*.

Table 3 Tabulation on *PDT*

Number of Data Packets (Number)	*PDT* (%)		
	FFO-WSN	Adaptive sampling strategy	Proposed TRRO-LDNNC Method
100	85	78	95
200	87	80	97
300	86	82	94
400	84	78	92
500	82	80	94
600	80	77	97
700	85	79	93
800	88	82	94
900	86	80	96
1000	89	82	98

The packet delivery ratio measurement is determined for FFO-WSN [1] and the Adaptive sampling strategy [2] and proposed TRRO-LDNNC Method given in above table 3. Simulation of *PDT* parameter is carried out with a comparative analysis between the proposed TRRO-LDNNC Method and two conventional methods. The above table 3 illustrates *PDT* measurement of TRRO-LDNNC Method is higher than the conventional techniques. Graph representation of *PDT* is depicted in figure 6.

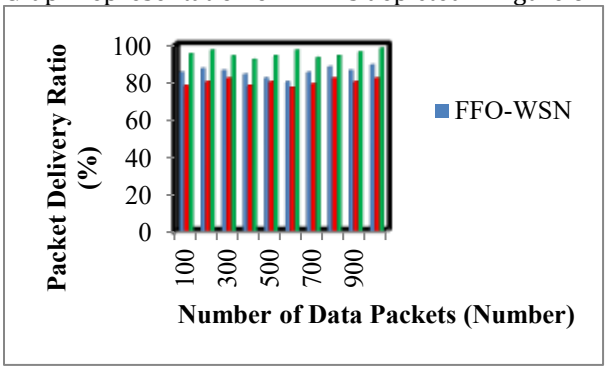

Figure 6 Performance Analysis based on *PDT*

According to dissimilar number of SN, finding outcomes for packet delivery ratio of three dissimilar methods are shown in figure 6. Result of *PDT* is achieved by TRRO-LDNNC Method than compared to two existing methods. TRRO-LDNNC Method efficiently increases *PDT* as broadcasting data packets from source to the destination. This is owing to using tobit regression to examine energy consumption and bandwidth consumption for efficient node classification. The neighboring resource efficient SN are chosen for data broadcast with high delivery ratio. This in turn helps to increase *PDT*. Thus, *PDT* of proposed TRRO-LDNNC is efficiently increased by 12%, and 19% than the [1], [2].

a. Packet Loss Rate

It is measured as total number of data packets lost at BS or sink node through the entire number of data packets broadcasted as of source node. It is expressed as:

$$PLR = \left(\frac{Dp\ Lost}{Dp\ sent}\right) * 100 \quad (12)$$

Where, '*PLR*' symbolizes the packet loss rate. '*Dp Lost*' represents data packets lost. '*Dp sent*' symbolizes the data packet sent. It is computed in percentage (%). Table 4 illustrates performance of *PLR*.

Table 4 Tabulation on *PLR*

	PLR (%)

Number of Data Packets (Number)	FFO-WSN	Adaptive sampling strategy	Proposed TRRO-LDNNC Method
100	15	22	5
200	13	20	3
300	14	18	6
400	16	22	8
500	18	20	6
600	20	23	3
700	15	21	7
800	12	18	6
900	14	20	4
1000	11	18	2

PLR measurement is determined on number of data packets for three methods such as FFO-WSN [1] and the Adaptive sampling strategy [2], and proposed TRRO-LDNNC Method shown in above table 4. The simulation of packet loss rate parameter is carried out with the comparative analysis between the proposed TRRO-LDNNC Method and two conventional methods. The above table 4 demonstrates that the packet loss rate measurement of the TRRO-LDNNC Method is lesser than the two conventional techniques.

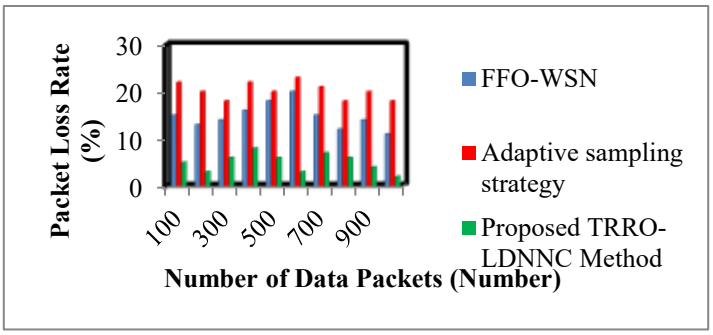

Figure 7 Performance Analysis based on Packet Loss Rate

According to dissimilar number of SN, finding outcomes for packet loss rate of three dissimilar methods are depicted in figure 7. Simulation result of *PLR* is obtained through comparative analysis among TRRO-LDNNC and two conventional techniques. TRRO-LDNNC Method efficiently minimizes packet loss rate as broadcasting data packets from the source to sink node. This is due to the application of tobit regression analysis for discovering resource effective SN with minimum energy consumption The neighboring resource effective SN are chosen for reducing loss rate. It aids to minimize *PLR*. Thus, *PLR* of TRRO-LDNNC Method efficiently reduced by 66% and 75% than the FFO-WSN [1] and Adaptive sampling strategy [2].

4.4 End-to-End Delay

It is defined as dissimilarity depending on difference among expected arrival time at sink node and observed arrival time of data packets. It is computed,

$$EED = [T_E - T_O] \quad (13)$$

Where, 'EED' represent the end-to-end delay. Delay is measured in milliseconds (ms). Table 5 illustrates result analysis on end-to-end delay.

Table 5 Tabulation on EED

Number of Data Packets (Number)	EED (ms)		
	FFO-WSN	Adaptive sampling strategy	Proposed TRRO-LDNNC Method
100	38	45	25
200	40	49	28
300	42	53	32
400	45	56	35
500	48	60	38
600	52	62	41
700	55	66	44
800	58	69	47

900	60	72	50
1000	63	75	52

EED measurement is determined on number of data packets for three methods such as FFO-WSN [1] and Adaptive sampling strategy [2], and proposed TRRO-LDNNC Method shown in above table 5. The simulation is carried out with the comparative analysis between the proposed TRRO-LDNNC Method and two conventional methods. Above table 5 shows that EED measurement of the TRRO-LDNNC Method is lesser than the conventional methods. Graph representation of EED measurement depicted in figure 8.

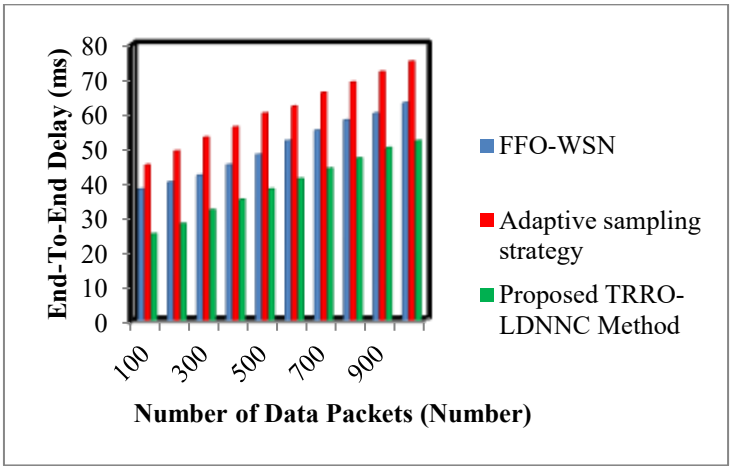

Figure 8 Performance Analysis based on EED

According to different number of sensor nodes, finding outcomes for EED result of the three dissimilar methods are depicted in figure 8. Simulation result of end-to-end delay is attained through comparative study among TRRO-LDNNC and two conventional methods. TRRO-LDNNC Method efficiently minimizes end-to-end delay as broadcasting data packets as of source to sink node. This is because of application of tobit regression analysis for discovery resource effective SN. The neighboring resource effective SN are recognized for reducing delay time. Thus, EED of TRRO-LDNNC is efficiently minimized by 23% and 36% than the FFO-WSN and Adaptive sampling strategy respectively.

6. Conclusion

Efficient data broadcasting performed the data communication through giving resources, handling connection as well as coordinating communication among IoT tools. A new method called TRRO-LDNNC method is introduced for performing resource optimized data transmission. TRRO-LDNNC Method collects the data packets from sensor nodes. Tobit Regression Analysis examines the energy consumption and bandwidth consumption for efficient node classification. The resource effective SN are considered for data broadcast. Manhattan distance finds the nearest neighbor node with the least distance for efficient data communication in WSN. By this way, data packets are broadcasted to base station in WSN. This helps to reduce delay and energy consumption during data transmission in wireless networks. Simulation is performed with various parameters. TRRO-LDNNC method obtains superior PDT and minimum EED and PLR through data broadcast when compared to other existing approaches. Limitation of the proposed method is failed to consider the cluster head selection. Also, the different metrics, such as network lifetime and throughput were not estimated for the data transmission performance. In future work, proposed technique will extended to apply new deep learning and optimization methods for selecting the cluster head to achieve better data transmission. In addition, the network lifetime and throughput will be computed to enhance the data transmission performance.

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