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MEAN SHIFT DEMING REGRESSION-BASED DEEP MULTILAYER PERCEPTIVE NEURAL LEARNING FOR RESOURCE OPTIMIZED DATA TRANSMISSION IN WSN

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ABSTRACT

A Wireless Sensor Network (WSN) is incorporated with multi-capabilities to sense, calculation, data gathering, and communication. The network consists of small sensor nodes which are capable of monitoring and processing the data from a particular geographical position and transmits it to a remote location i.e. sink node or Base Station (BS). During the communication, extending the lifetime and stability of WSN remains challenging issue. Therefore, resource efficiency is a crucial factor in WSN to extend the network lifetime. In order to develop a Mean Shift Deming Regression-based Deep Multilayer Perceptive Neural Learning (MSDR-DMPNL) Model for dual cluster head selection to perform resource optimized data transmission in WSN. MSDR-DMPNL model comprised five layers, namely one input, three hidden layers, and one output layer for performing energy-efficient data transmission. The number of sensor nodes is considered as input in the input layer. After that, the energy and memory of the sensor node are computed in the hidden layer 1. Then, the information is transmitted to the hidden layer 2. In that layer, Mean Shift Node Clustering is carried out to perform the clustering process based on energy and memory. After that, the number of clusters is transmitted to the hidden layer 3 where Deming Regression is performed to select the dual cluster head (i.e., primary cluster head and secondary cluster head) in every cluster. Then the sensor node transmits the data packets to the primary cluster head through a neighboring node with high bandwidth availability. The primary cluster head transmits the collected data packets to the secondary cluster head. Finally, it transmits the received data packets to the base station. In this way, efficient resource-efficient data transmission is carried out. Simulation is conducted on factors such as clustering accuracy, energy consumption, packet delivery ratio, and delay with respect to a number of sensor nodes and packets.

***Keywords**: WSN, Resource Optimized Data Transmission, Deep Multilayer Perceptive Neural Learning, Deming Regression, Mean Shift Node Clustering.*

1. INTRODUCTION

WSNs include a set of distributed nodes to monitor and record the environmental data in a random or deterministic manner. The sensed data are transmitted into the base station. However, the data transmission between the nodes in an effective way is not feasible due to various difficult factors such as mobility; improve the life span of WSNs, and so on. Clustering is a well-known technique to create the transmission of data more effective. The clustering model partitions the sensor nodes into a variety of clusters. Every cluster in the wireless network has a unique cluster head and it sends the information to the base station.

A Firefly Replaced Position Update in Dragonfly (FPU-DA) was introduced in [1] to select the optimal cluster head for energy-efficient data communication. However, the higher delivery was not obtained with a minimum delay during the data transmission. A High-Quality Clustering Algorithm using fuzzy logic for Wireless Sensor Networks (HQCA-WSN) was designed in [2] to improve the energy consumption and enhance the network lifetime. But, the designed algorithm failed to comprise more parameters such as bandwidth, memory for optimal cluster head selection.

A novel energy-efficient clustering method was developed in [3] based on a genetic algorithm for cluster head selection. The clustering method was not efficient for cluster head selection with lesser complexity. A Fuzzy Multi Cluster-Based Routing with a Constant Threshold (FMCR-CT) was developed in [4] for transmission of data to the base station. But the algorithm failed to increase reliable data transmission.

A Deep Reinforcement Learning method was introduced in [5] to improve the throughput and minimizes the delay. But the accurate clustering was not performed. An Enhanced Clustering Hierarchy (ECH) model was developed in [6] to attain higher energy efficiency. But the model failed to analysis on the network lifetime maximization. In order to enhance the network lifetime, a hybrid algorithm was introduced in [7]. The designed algorithm failed to efficiently perform data transmission with lesser delay.

An optimal cluster head selection method was introduced in [8] to obtain the minimal end-to-end delay as well as packet drop during the data transmission. But the multiple resources are not considered for selecting the cluster head. A novel energy-optimization routing protocol was designed in [9] using dynamic hierarchical clustering to increase the network data transmission with lesser delay. But the algorithm failed to minimize the complexity of the protocol.

Fixed-Parameter Tractable (FPT) approximation algorithm was designed in [10] for energy-efficient routing between the cluster heads. But the designed algorithm failed to improve and evaluate the cluster accuracy. A Fuzzy Logic-based Effective Clustering (FLEC) algorithm was introduced in [11] for data transmission between the sensor node and cluster head. But the algorithm failed to focus on the dynamic and heterogeneous WSN.

A novel clustering protocol based on the meta-heuristic model was developed in [12] for enhancing the network lifetime. The approach failed to improve the network throughput with the various energy harvesting constraints. An Energy-Coverage Ratio Clustering Protocol (ECRCP) was developed in [13] for decreasing energy consumption and prolong the network lifetime. The designed algorithm failed to consider the multiple resources for solving the cluster-based data transmission.

A novel clustering algorithm was introduced in [14] for selecting the CHs using the Grey Wolf Optimizer (GWO). The designed algorithm was not efficient to improve the performance of clustering accuracy. Combining Election and Routing Amongst Cluster Heads (CER-CH) was introduced in [15] to improve the network lifespan. But the delay aware data transmission was not performed. A three-level heterogeneous clustering method was developed in [16] focuses on the effective cluster head selection for increasing the system performance. An improved K-means clustering algorithm was designed in [17] for intra-cluster communication to construct the numerous clusters. However, deep resource-efficient learning was not performed to improve the communication.

A reliability-based enhanced technique was introduced in [18] to select the cluster head using fuzzy logic. Though the designed technique improves the delivery ratio and minimizes the delay, the performance of clustering accuracy was not improved. A sampling-based spider monkey optimization algorithm was developed in [19] to perform cluster head selection and improve energy efficiency. The designed algorithm was not reduces the delay. An Optimal energy-efficient cluster head selection algorithm was designed in [20] to increase the efficiency of improving lifetime and throughput. The designed algorithm failed to perform the analysis using a number of nodes and high network size.

In order to solve the above-said issues, a novel MSDR-DMPNL model is introduced to improve resource-efficient data transmission. The novel contribution of the proposed MSDR-DMPNL model is listed below,

- To improve the resource-efficient data transmission in WSN, an MSDR-DMPNL model is designed based on the clustering and cluster head selection using Deep Multilayer Perceptive Neural Learning.
- A Mean Shift node clustering is applied to the hidden layer of the deep learning to partition the network into the number of clusters based on the residual energy and memory availability. The clustering process is performed based on mean and deviation.
- To improve data delivery and minimize the delay, a Deming Regression is applied in the MSDR-DMPNL model to select the dual cluster head (i.e., primary cluster head and secondary cluster head) for every cluster. Then the sensor node distributes the data packets to the primary cluster head via a

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neighboring node with higher bandwidth availability.

- The simulation results were conducted to evaluate the analysis of the MSDR-DMPNL model in terms of clustering accuracy, energy consumption, data delivery rate, and minimum delay.

The remainder of this manuscript is arranged into different sections as follows. Section 2 introduces the proposed MSDR-DMPNL with a neat diagram. Section 3 reports the simulation results and a comparison of the proposed MSDR-DMPNL with similar existing methods are presented in section 4. Finally, the conclusions are drawn in Section 5.

2. MEAN SHIFT DEMING REGRESSION-BASED DEEP NEURAL LEARNING MODEL

The Mean Shift Deming Regression-based Deep Multilayer Perceptive Neural Learning (MSDR-DMPNL) is introduced. The main objective of the MSDR-DMPNL Model is to improve resource optimization during data communication between the sensor nodes and the sink node. The system model of the proposed MSDR-DMPNL is described. The WSN is denoted as a graph $g\,(v,e)$ where $'v'$ symbolizes a sensor nodes'$SN = s_1, s_2, \dots, s_n$' deployed in the square area $n * n$ to monitor the environmental conditions and frequently sent to the sink node (SN). In the graph, 'e' represents edges i.e., links between the nodes. For each distributed sensor nodes, the residual energy '$RE(SN)$' and memory availability '$MA(SN)$' is measured to partition the network into the number of clusters. For every cluster, primary cluster head 'PCH' and secondary cluster head 'SCH' are selected for transmitting the data packets $dp_1, dp_2, \dots . dp_n$ from sender to sink node.

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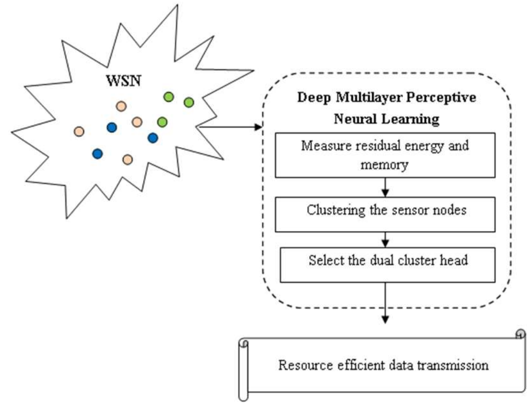

Figure 1 Architecture of The Proposed MSDR-DMPNL Method

Figure 1 describes the architecture diagram of the proposed MSDR-DMPNL. The designed MSDR-DMPNL includes the processes, such as clustering, cluster head selection to obtain resource efficient data transmission in WSN.

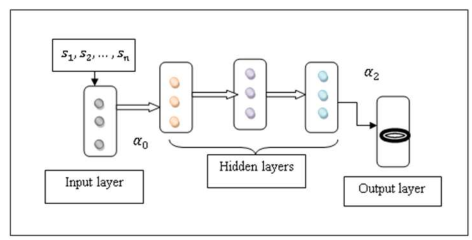

Figure 2 Construction of Deep Multilayer Perceptive Network

Figure 2 depicts the structure of the deep multilayer perceptive network. The network comprises multiple layers such as one input layer, one output layer, and multiple hidden layers. The layers are connected through the neurons like the nodes. The nodes in one layer are connected to form the entire network. The layers are connected with the adjustable weight. As shown in figure 2, α_0 denotes an adjustable weight between the input and hidden layer α_2 indicates an adjustable weight between the hidden and output layer.

Let us consider the number of sensor nodes '$SN = s_1, s_2, \dots, s_n$ are taken as input. The activity of the neuron at the input layer is expressed as given below,

$$z(t) = \sum_{i=1}^{n} s_i(t) * \alpha_0 + m \tag{1}$$

Where '$z(t)$' indicates the input layer output. '$s_i(t)$' denotes the number of sensor nodes,' α_0

symbolizes the initial weight at the input layer, 'm' symbolizes the bias stored the value is '1'. Then the input is transferred into the first hidden layer. For each input, the energy and memory availability is measured as given below,

Initially, the entire sensor node has a similar energy level. Due to the sensing process of the node, the initial energy level gets reduced and the remaining energy of the sensor nodes is calculated as given below,

$$RE(SN) = \sum_{i=1}^{n}[TE(SN_i)] - [CE(SN_i)] \quad (2)$$

From (2), $RE(SN)$ indicates residual energy, $TE(SN_i)$ represents the total energy of the nodes, $CE(SN_i)$ symbolizes the consumed energy of the nodes. Similarly, the other resource is the memory availability measured as given below,

$$MA(SN) = \sum_{i=1}^{n}[TM(SN_i)] - [CM(SN_i)] \quad (3)$$

From (3), $MA(SN)$ indicates a memory availability 'MA' of sensor node 'SN', $CM(SN_i)$ denotes a memory consumption of sensor nodes. Then the measured residual energy and memory availability of the sensor nodes are given to the hidden layer 2. In that layer, the clustering process is carried out to group the sensor nodes.

The mean shift clustering technique partitions the number of sensor nodes into different clusters based on mean and deviation. The number of clusters is identified based on the number of sensor nodes. For each cluster, the mean is assigned based on the weighted sum of a number of sensor nodes.

$$\mu = \frac{\sum_{i=1}^{n} w_i s_i}{\sum_{i=1}^{n} w_i} \quad (4)$$

Where, μ denotes a mean of the cluster, w_i denotes a weight, s_i represents the number of sensor nodes. For each mean (i.e. cluster center), the nearby sensor nodes are grouped based on the estimated resources into the cluster as give below,

$$R = \exp\left(-\frac{1}{2\,d^2} * \left\| s_i - \mu_j \right\|^2\right) \quad (5)$$

From (5), R represents clustering results, d denotes a deviation from its mean, $\left\| s_i - \mu_j \right\|^2$ denotes a distance between the mean of the clusters 'μ_j' and the sensor nodes 's_i'. Followed by, the node which is closer to the mean is grouped into the particular cluster. In this way, all the sensor nodes are grouped into a particular cluster.

- **Deming regression-based Cluster head selection**

After the clustering process, the cluster head selection is performed to perform efficient data transmission. The responsibility of the cluster head is to communicate with the other sensor nodes of its cluster. The cluster head collects the data from the sensor nodes and forwards the aggregated data to the base station. This helps to reduce the delay of data transmission from source to sink node. The proposed MSDR-DMPNL uses the Deming regression function that helps to find the best resource-efficient node as a primary cluster head and a second efficient node as a secondary cluster head. The regression function analyzes the resources of the sensor nodes such as residual energy and memory availability.

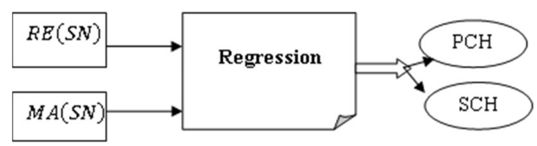

Figure 3 Deming Regression Based Cluster Head Selection

As shown in figure 3, the regression based cluster head selection is performed to analyze the sensor nodes based on the residual energy and memory availability.

$$Y_i = \delta_0 + \delta_1 [R_k (SN_i)] \quad (6)$$

From (6), Y_i denotes a resource estimation of sensor node SN_i in a particular cluster, δ_0 and δ_1 indicates the regression coefficients, $R_k (SN)$ denotes resources of the sensor nodes i.e. residual energy $[RE(SN)]$, memory availability $[MA(SN)]$. Based on the regression analysis, the node that has maximum residual energy and memory availability is chosen as the primary cluster head. Similarly, the other resource-efficient node is chosen as the secondary cluster head.

$$\mathrm{R} = \arg\max [\ RE(SN) \ \&\& \ MA(SN)] \quad (7)$$

Where R denotes a regression output, arg max denotes an argument of maximum function. In this way, the cluster head is chosen for efficient data transmission. The sensor node transmits the data packets to the primary cluster head via neighboring higher bandwidth availability sensor nodes.

$$BW_a = [T_{BW}] - [C_{BW}] \quad (8)$$

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Where, BW_a denotes a bandwidth availability, T_{BW} symbolizes the total bandwidth, C_{BW} indicates the consumed bandwidth. The primary cluster head transmits the collected data packets to the secondary cluster head. Finally, it transmits the received data packets to the base station.

The output of the hidden layer is expressed as given below,

$$G(t) = \sum_{i=1}^{n} s_i(t) * \alpha_0 + [\alpha_1 * g_i(t)] \quad (9)$$

From (9), '$G(t)$' indicates the hidden layer output, 'α_0' denotes the adjustable weight between input and hidden layer, $g_i(t)$ denotes an output of the previous hidden layer, α_1 denotes the adjustable weight between the hidden layer. The result of the output layer is formulated as,

$$Z(t) = [\alpha_2 * G(t)] \quad (10)$$

Where, '$Z(t)$' represents the output layer result, 'w_{ho}' represents the weight allocated between the hidden and output layer. In this way, resource-efficient data transmission is performed in WSN. The algorithmic description of the proposed MSDR-DMPNL process is explained below,

Algorithm 1: Mean Shift Deming Regression-based Deep Multilayer Perceptive Neural Learning
Input: Number of sensor nodes $SN = s_1, s_2, \dots, s_n$, Number of data $D_i = d_1, d_2, .., d_n$ **Output:** Increase the resource-efficient data transmission
Begin **Step 1. Number of nodes** $SN = s_1, s_2, \dots, s_n$ taken as input at the input layer **Step 2: For each** node s_i **// hidden layer 1** **Step 3:** Measure the $RE(SN)$ and $MA(SN)$ **Step 4**: Initialize the number of clusters **Step 5: For** each cluster' j' **Step 6:** calculate mean 'μ' **Step 7: end for** **Step 8: end for** **Step 8: For each** μ **Step 9: For** each sensor node **Step 10**: Calculate the distance 'R' **Step 11**: Group sensor node into clusters j based on the distance R **Step 12**: **end for** **Step 13**: **End for** **Step 14: for each** cluster **Step 14: for each** node **Step 15: Analyze the resources 'Y_i'** **Step 16:** Find resource-efficient node $R = \arg\max [\ RE(SN) \&\& MA(SN)]$ **Step 17:** Select primary and secondary cluster head **Step 18:** Send data packets $D_i = d_1, d_2, .., d_n$ **Step 19: end for** **Step 20: end for** **End**

Algorithm 1 describes the step-by-step process of the proposed MSDR-DMPNL technique for resource-efficient data transmission in WSN. The deep multilayer perceptive learning algorithm comprises many layers to learn the sensor nodes with their resources. The sensor nodes are given as input to the first hidden layer where the residual energy and memory availability is measured. Then the estimated values are given to the next hidden layer. In that layer, the mean shift clustering technique is applied to group the sensor nodes based on the resources such as residual energy and memory availability. Finally, the Deming regression is applied to analyze the resource of the sensor nodes and find the primary and secondary cluster head. The sensor nodes send the information to the primary cluster head of their cluster. Then the secondary cluster head transmits the information into the base station. Based on the analysis, resource-efficient data communication is achieved with lesser delay.

3. SIMULATION SETTINGS

The simulation of the proposed MSDR-DMPNL technique and two other existing techniques namely FPU-DA [1], HQCA-WSN [2] are implemented using the NS2 simulator. The simulation is conducted with the 500 sensor nodes deployed in a squared area of 1100 * 1100 m^2. The sensor nodes are randomly distributed at the speed of 0 to 20m/sec. The simulation time is set as 300 sec. For efficient data transmission, the Dynamic Source Routing (DSR) protocol is used in the simulation setup. The simulation parameters and the values are shown in Table 1.

Table 1 Simulation Parameters

S. No	Parameter	Values
1	Network area	1100 * 1100 m^2
2	Number of nodes	500

3	Initial energy	0.5 J
4	Packet	15/iteration
5	Bandwidth	10 bit/s
6	Data packet size	2000 bits
7	Communication range	30m
8	Routing protocol	DSR

4. RESULTS AND DISCUSSIONS

The simulation results of the proposed MSDR-DMPNL and existing methods FPU-DA [1], HQCA-WSN [2] are discussed in this section with different performance metrics such as clustering accuracy, energy consumption, packet delivery ratio, and an end to end delay. The obtained results are discussed with the help of a table or graphical representation.

Clustering Accuracy: The clustering accuracy is measured as the ratio of a number of clusters accurately formed to the total number of clusters initialized. The mathematical formulation of clustering accuracy is measured as given below.

$$CA = \left[\frac{C_{af}}{TC}\right] * 100 \qquad (11)$$

Where 'CA' denotes a clustering accuracy ', 'C_{af}' denotes the number of clusters accurately being formed, TC denotes a total clusters 'TC' in the network. It is measured in terms of percentage (%).

Table 2 Clustering Accuracy

Number of Sensor nodes	Clustering accuracy (%)		
	MSDR-DMPNL	FPU-DA	HQCA-WSN
50	90	80	70
100	93.75	75	68.75
150	90.47	71.42	66.66
200	87.5	70.83	66.66
250	85.18	70.37	59.25
300	83.33	70	56.66
350	82.35	67.64	55.88
400	80.55	66.66	55.55
450	78.94	65.78	55.26
500	77.5	65	55

Table 2 describes the simulation of the clustering accuracy regarding the number of sensor nodes taken in the ranges from 50 to 500. The accuracy is measured using three MSDR-DMPNL and existing methods FPU-DA [1], HQCA-WSN [2]. The table value noticed that the clustering accuracy of MSDR-DMPNL is higher than the other two conventional methods. For example, '50' sensor nodes are considered to conduct the simulation and the number of clusters is initialized as'10', and the number of cluster being formed is '9' and the clustering accuracy is 90% using MSDR-DMPNL. Similarly, the clustering accuracy of existing [1] [2] is 80% and 70% respectively. The various runs are carried out along with different inputs. The average of ten results indicates that the clustering accuracy of MSDR-DMPNL is increased by 21% when compared to [1] and 40% when compared to [2].

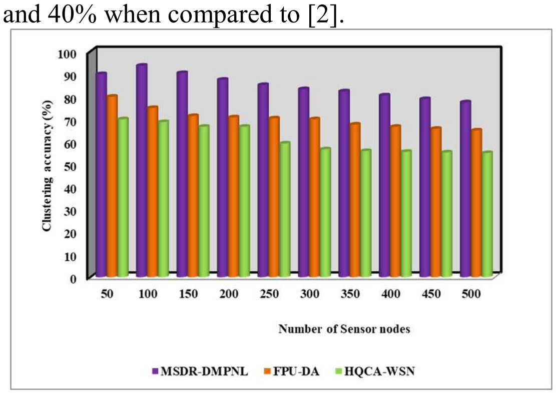

Figure 4 Clustering Accuracy Varies With The Number Of Sensor Nodes

Figure 4 given above illustrates the clustering accuracy versus numbers of sensor nodes distributed in the range of 50 to 500 for conducting the simulation. The graphical plot indicates that the clustering accuracy of three different methods MSDR-DMPNL and two other existing FPU-DA [1], HQCA-WSN [2] are represented by three different colors namely violet, orange and green respectively. But the observed results indicate that the MSDR-DMPNL achieves higher clustering accuracy than the conventional methods. The reason behinds that the MSDR-DMPNL uses the Mean Shift Clustering to group the sensor nodes based on the energy and memory availability. The proposed Mean Shift Clustering-based deep learning concept accurately group the sensor nodes into a particular cluster based on mean and deviation.

Energy Consumption: The energy consumption is measured as the amount of energy consumed by sensor nodes during the clustering and is mathematically formulated as given below.

$$EC = \sum_{i=1}^{n} sn_i * EC[p(SN_1, SN_2, \ldots, SN_n)] \qquad (12)$$

Where, EC denotes energy consumption, sn_i denotes the number of sensor nodes considered for

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simulation, $EC[p(SN_1, SN_2, \ldots, SN_n)]$ denotes energy consumed in forming the cluster according to the partitioning of different sensing nodes. It is measured in terms of joules 'J'.

Table 3 Energy Consumption

Number of Sensor nodes	Energy Consumption (joules)		
	MSDR-DMPNL	FPU-DA	HQCA-WSN
50	12.5	18	20
100	14	20	22
150	15.75	21	24
200	18	22	26
250	20.5	23.25	27.5
300	21.6	25.5	28.5
350	24.85	28.7	30.45
400	28	32	34
450	30.15	33.75	35.1
500	35	39	41

The simulation assessment of the energy consumption using MSDR-DMPNL and two other existing FPU-DA [1], HQCA-WSN [2] is depicted in Table 3. The reported results of the MSDR-DMPNL indicate the energy consumption is found to be reduced than the conventional methods. This is proved through statistical estimation. With '50' numbers of sensor nodes considered to calculate the energy consumption of MSDR-DMPNL is $12.5J$ and the energy consumption other two existing methods are $18J$ and $20J$ respectively. For each method, ten runs are carried out with the number of sensor nodes. The obtained results of the proposed technique are compared to the existing methods. The comparison results show that the MSDR-DMPNL provides improved performance in terms of minimizing energy consumption. The average results indicate that the overall energy consumption of MSDR-DMPNL is comparatively minimized by 21% and 28% than the existing methods.

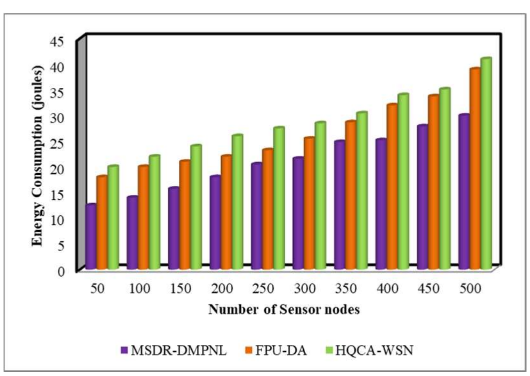

Figure 5 Energy Consumption Varies With The Number Of Sensor Nodes

Figure 5 depicts the energy consumption of the proposed DSBAFRODCHS technique and existing methods namely FPU-DA [1], HQCA-WSN [2]. From the graphical plot, it is inferred that the energy consumption is inversely proportional to the number of sensor nodes. The significant reason for the proposed DSBAFRODCHS technique is due to the identification of resource-efficient sensor nodes based on the residual energy and memory availability. The sensor node consumes lesser energy and having the maximum residual energy is selected for data transmission. In addition, the resource-efficient cluster head selection also improves the data transmission to improve the network lifetime.

Packet Delivery Ratio: It is defined as a percentage ratio of data packets received at the destination to the number of data packets received at the base station and is mathematically formulated as given below.

$$PDR = \frac{DP_{received}}{DP_{sent}} * 100 \quad (13)$$

Where, PDR denotes a packet delivery ratio, '$DP_{received}$' denotes a data packets received and ''DP_{sent}' represents the data packet sent. It is measured in terms of percentage (%).

Table 4 Packet Delivery Ratio

Number of data packets	Packet delivery ratio (%)		
	MSDR-DMPNL	FPU-DA	HQCA-WSN
15	93.33	73.33	66.66
30	93.33	83.33	80
45	91.11	80	75.55
60	90	83.33	76.66
75	92	84	80
90	91.11	83.33	80
105	90.47	80	77.14
120	91.66	83.33	79.16
135	89.62	81.48	77.77
150	92.66	85.33	80

Table 4 performance results of the MSDR-DMPNL technique over existing methods namely FPU-DA [1], HQCA-WSN [2] are recorded. The simulation results of the proposed MSDR-DMPNL technique are compared to two conventional techniques by varying the number of data packets. Let us consider the number of data packets is 15 data packets. Among 15 data packets, 14 data packets are effectively received at destination and the delivery ratio of the MSDR-DMPNL technique is 93.33%. Whereas 11 and 10 data packets are correctly received at destination and the delivery ratio are 73.33% and 66.66% using FPU-DA [1], HQCA-WSN [2]. Similarly, various runs are performed along with the number of data packets. The average of ten results indicates the packet delivery ratio is significantly improved by 12% using the MSDR-DMPNL technique when compared to FPU-DA [1] and also increased by 19% when compared to HQCA-WSN [2].

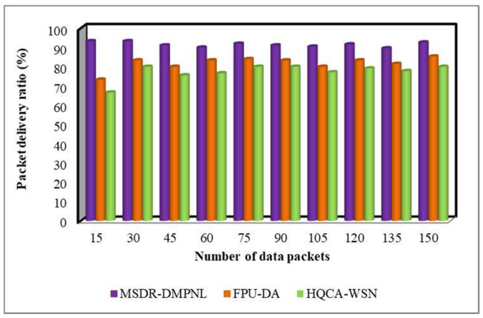

Figure 7 Packet Delivery Ratio Varies With The Number Of Data Packets

Figure 7 demonstrates the graphical representation of the packet delivery ratio versus the number of data packets from 15 to 150. Figure 7 given above illustrates the comparative performance of the packet delivery ratio for 150 different sets of data packets. As a result, 150 data packets are given as input in 'x' axis and the packet delivery ratio is observed in the 'y' axis. This is because the deep learning approach uses the clustering concept to group the sensor nodes. In addition, the Deming regression function is applied to find the resource-efficient cluster head among the multiple sensor nodes. The primary cluster head node sends the secondary cluster head and it transmits to the base station. Finally, the data packets are successfully transmitted to the base station through the cluster head. As a result, a higher packet delivery ratio is achieved.

End-to-end delay: It is defined as a difference between the actual arrival time of data packets and the observed arrival time of data packets. Therefore, the delay is mathematically formulated as given below.

$$D = AT_{ob} - AT_{act} \tag{14}$$

Where Ddenotes a delay, 'AT_{ob}' denotes an observed arrival time, AT_{act} denotes an actual arrival time. It is measured in terms of milliseconds (ms).

Table 5 Packet Delivery Ratio

Number of data packets	End to end delay (ms)		
	MSDR-DMPNL	FPU-DA	HQCA-WSN
15	7	11	13
30	9	12	15
45	10	13	16
60	11	14	17
75	12	15	18
90	13	16	20
105	15	18	22
120	16	20	23
135	17	21	25
150	18	22	26

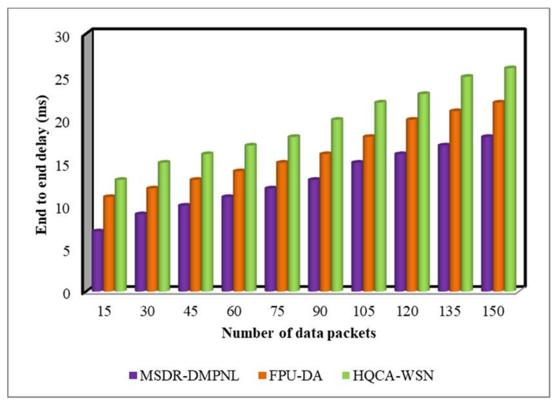

Figure 8 End To End Delay Varies With The Number Of Data Packets

Table 5 and figure 8 illustrate the simulation evaluation results of end-to-end delay versus the number of data packets. As revealed in the graph as well as table, increasing the count of input data packets and simultaneously end to end delay gets increased for all the three methods. Among the three methods, the end-to-end delay is found to be minimal by applying the MSDR-DMPNL technique when compared to the conventional methods. The significant reason is that applying the cluster-based data transmission to improve the delivery and minimizes the end-to-end delay. This is proved by statistical valuation by considering the 15 data packets to compute end-to-end delay. The delay of data delivery using the MSDR-DMPNL is $7ms$ and the delay of the other two methods [1] [2] are $11ms$ and $13ms$ respectively. Likewise, the nine runs are performed with various counts of data packets. The overall results of the proposed MSDR-DMPNL are evaluated with the results of existing methods. The comparison results prove that the end-to-end delay of the MSDR-DMPNL significantly minimized by 22% when compared to [1] and 35% when compared to [2].

5. CONCLUSION

In this paper, a novel resource-efficient model called MSDR-DMPNL is introduced for improving the network lifetime with increased data delivery and minimizes the delay. The MSDR-DMPNL model comprises the many layers to learn the given input and find the resource-efficient sensor nodes based on residual energy and memory availability. The Mean Shift Clustering algorithm is applied to perform the clustering process based on energy and memory. After the clustering process, the cluster head is selected using Deming Regression based on the maximum residual energy and memory availability. Then the sensor node transmits the data packets to the primary cluster head through a neighboring sensor node that having higher bandwidth availability. This helps to improve the data delivery with minimum delay. The comprehensive simulation is conducted to analyze the performance of the MSDR-DMPNL model with the existing two algorithms based on different metrics. The observed result shows that the proposed MSDR-DMPNL technique is more efficient than the earlier ones, having higher clustering accuracy, data delivery rate, and minimum energy consumption as well as delay.

REFERENCES

[1] Turki Ali Alghamdi, “Energy-efficient protocol in wireless sensor network: optimized cluster head selection model”, Telecommunication Systems, Springer, Volume 74, 2020, Pages 331–345

[2] Amir Abbas Baradaran and Keivan Navi, “HQCA-WSN: High-quality clustering algorithm and optimal cluster head selection using fuzzy logic in wireless sensor networks”, Fuzzy Sets and Systems, Elsevier, Volume 389, 15 June 2020, Pages 114-144

[3]Raju Pal, Subash Yadav, Rishabh Karnwal and Aarti, “EEWC: energy-efficient weighted clustering method based on genetic algorithm for HWSNs”, Complex & Intelligent Systems, Volume 6, 2020, Pages 391-400

[4] Armin Mazinani and Sayyed Majid Mazinani, Mostafa Mirzaie, “FMCR-CT: An energy-efficient fuzzy multi cluster-based routing with a constant threshold in wireless sensor network”, Alexandria Engineering Journal, Elsevier, Volume 58, Issue 1, 2019, Pages 127-141

[5] Ramadhani Sinde , Feroza Begum, Karoli Njau and Shubi Kaijage , “Refining Network Lifetime of Wireless Sensor Network Using Energy-Efficient Clustering and DRL-Based Sleep Scheduling”, Sensors, Volume 20, 2020, Pages 1-26

[6] Hassan El Alami and Abdellah Najid, “ECH: An Enhanced Clustering Hierarchy Approach to Maximize Lifetime of Wireless Sensor Networks”, IEEE Access, Volume 7, 2019, Pages 107142 – 107153

[7] Kale Navnath DattatrayaK. Raghava Rao, “Hybrid based cluster head selection for maximizing network lifetime and energy efficiency in WSN”, Journal of King Saud University - Computer and Information Sciences, Elsevier, 2019, Pages 1-11

[8] Jayashree Agarkhed, Patil Yogita Dattatraya and Siddrama Patil, “Multi-QoS constraint multipath routing in cluster-based wireless sensor network”, International Journal of Information Technology, Springer, 2020, Pages 1-12

[9] Zhidong Zhao, Duoshui Shi, Guohua Hui, and Xiaohong Zhang, “An Energy-Optimization Clustering Routing Protocol Based on Dynamic Hierarchical Clustering in 3D WSNs”, IEEE Access , Volume 7, 2019, Pages 80159 – 80173

[10] Ramin Yarinezhad , Seyed Naser Hashemi, “A routing algorithm for wireless sensor networks based on clustering and an fpt-approximation algorithm”, Journal of Systems and Software, Elsevier, Volume 155, 2019, Pages 145-161

[11] Akshay Verma, Sunil Kumar, Prateek Raj Gautam, Tarique Rashid, and Arvind Kumar , “Fuzzy Logic Based Effective Clustering of Homogeneous Wireless Sensor Networks for Mobile Sink”, IEEE Sensors Journal , Volume 20, Issue 10, 2020, Pages 5615 – 5623

[12] Yu Han, Gang Li, Rui Xu, Jian Su, Jian Li, Guangjun Wen, “Clustering the Wireless Sensor Networks: A Meta-Heuristic Approach”, IEEE Access , Volume 8, 2020, Pages 214551 – 214564

[13] Mengjia Zeng , Xu Huang , Bo Zheng , and Xiangxiang Fan, “A Heterogeneous Energy Wireless Sensor Network Clustering Protocol”, Wireless Communications and Mobile

Computing, Hindawi, Volume 2019, 2019, Pages 1-11
[14] S. M. Mahdi H. Daneshvar, Pardis Alikhah Ahari Mohajer, Sayyed Majid Mazinani, “Energy-Efficient Routing in WSN: A Centralized Cluster-Based Approach via Grey Wolf Optimizer”, IEEE Access, Volume 7, Pages 170019 – 170031
[15] Matteo Micheletti, Leonardo Mostarda, Alfredo Navarra, “CER-CH: Combining Election and Routing Amongst Cluster Heads in Heterogeneous WSNs”, IEEE Access, Volume 7, 2019, Pages 125481 – 125493
[16] Rahul Priyadarshi, Piyush Rawat, Vijay Nath, Bibhudendra Acharya and N. Shylashree, “Three level heterogeneous clustering protocol for wireless sensor network”, Microsystem Technologies, Volume 26, 2020, Pages 3855-3864
[17] Salim El Khediri, Walid Fakhet , Tarek Moulahi, Rehanullah Khan, Adel Thaljaoui, Abdennaceur Kachouri, “Improved node localization using K-means clustering for Wireless Sensor Networks”, Computer Science Review, Elsevier, Volume 37, 2020, Pages 1-9
[18] S. Murugaanandam and Velappa Ganapathy, “Reliability-Based Cluster Head Selection Methodology Using Fuzzy Logic for Performance Improvement in WSNs”, IEEE Access , Volume 7, 2019, Pages 87357 – 87368
[19] Jin-Gu Lee , Seyha Chim and Ho-Hyun Park, “Energy-Efficient Cluster-Head Selection for Wireless Sensor Networks Using Sampling-Based Spider Monkey Optimization”, Sensors, Volume 19, 2019, Pages 1-18
[20] G. Saranraj, K. Selvamani, and G. R. Kanagachidambaresan , “Optimal Energy-Efficient Cluster Head Selection (OEECHS) for Wireless Sensor Network”, Journal of The Institution of Engineers (India): Series B, Springer, Volume 100, 2019, Pages 349-356