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ENHANCING EFFICIENCY IN WIRELESS SENSOR NETWORKS THROUGH CLUSTERING AND ROUTING OPTIMIZATION

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Abstract

This research aims at incorporating Wireless Sensor Networks (WSNs) with deep learning to enable farmers to receive early notification about their produce. It presents the structured combined model which is used to solve the problem of energy consumption and the problem of reliability of communication in WSNs. The component include are network model, energy consumption model, a cluster head selection using k-medoids algorithm and route optimization using adaptive sail fish (AS) algorithm. To improve the route performance, the framework has both Deep Feedforward Neural Network (DFFNN) and the Buffalo Algorithm (BA). The WSN comprises the Base Station (BS), low-performance (LP) sensors and High-performance (HP) sensors with the HP sensors performing the duty of the Cluster Heads. Energy consumption is assumed proportional with the data transmission distance and path loss; K-Medoids clustering optimizes efficiency of communication and minimizes power utilization. Some of the results of analysis in MATLAB R2023b show that the proposed model provides enhancements in terms of energy efficiency, residual energy, and packet delivery ratio through simulations.

Keywords:

Sensor Networks, Clustering, Routing, Sailfish Optimization Algorithm, Deep Neural Networks

1. INTRODUCTION

The WSNs [1] are made up of small and cheaply-priced sensor nodes; these are the basic components used for transmitting data to a main processing station from different locations. These nodes act as a drone swarm which organizes into a multi-hop network, able to adjust, and even transmit the compressed information to a central base station [2]. Multimedia WSNs, those in which the conveyance of multimedia data like images or videos is supported, identify their uses in industrial sectors, agricultural, military monitoring, smart buildings and health insurance. Nonetheless, processing multimedia requires considerable resources due to the size and nature of this data. Energy conservation is, especially, vital for sensor nodes (SNs) in WSNs to prolong their lifetime, since they consume up energy mostly in pack transmission [3].

Unlike WSNs whose sensor nodes are directly about power source, batteries, the dilemma of its maintenance becomes painful because of the difficulty of re-charging it. As a result, design optimization algorithms that increase network lifespan and peak efficiency is key [4]. Clustering, a central power management function in WSNs, is to partition the network into clusters in such a manner each cluster has its CH. This is achieved through the collection of data from various nodes and the same transported to the base station by the CHs which minimizes the traffic load of the base station [5]. It achieves the purpose of power savings, mainly in situations where power is the key, limited resource. The clustering algorithm works in rounds, formed by CH which perform in two phases, stabilization and formation, while entities are divided into clusters [6]. The CH while collecting data from the SNs communicates it with the BS through the data aggregation algorithms. The choice of an appropriate CH is the key decision, permitting preservation of energy efficiency during clustering methods.

An algorithm such as K-Means determines the best number of clusters and their centroid by minimizing the Euclidean distances between data points and centroid [7]. The K-medoids technique was to create a more stable network architecture by grouping initial nodes to restrain the effect of outliers [8]. Using the elephant herding optimization technique, the efficient transmission of data is achieved by reducing latency and maximizing throughput [9]. Nevertheless, this scheme leads to a sharp increase in total power consumption, which could limit the network's lifetime. The previous versions have been struggling with the issues of packet loss rate, network longevity, packet delivery rate (PDR), performance, power efficiency, and latency. Moreover, the fact that WSNs have limited communication and computing abilities makes data collection quite complex.

This paper has made a novel contribution to the field of WSNs with DFFNN being the proposed testing method that optimizes network efficiency by using clustering and routing algorithms. Besides, it illustrates the efficiency of the technique through an in-depth breakdown of outcomes and analysis; thus fostering the cognizance of the WSN optimization tactics.

1.1 PROBLEM STATEMENT

WSNs (wireless sensor networks) face problems like energy consumption, choosing the head of the cluster and route selection in their network so their performance suffers and the network is not reliable. Today, even though we have had several approaches they are not always effective and reliable in overcoming these issues. For that reason solutions needed a coherent framework which crosses advanced algorithms and machine learning techniques to find the optimum WSNs.

This study is directed towards establishing this network of structures to encourage power efficiency, enhance data transmission reliability and prolong network lifetime in WSNs. The field experiment primarily targets developing models suitable for the links, energy usage, and group formation on the overall network, as well as the optimization of the routing algorithms that are effectively related to network performance improvement, which is based on energy consumption, residual energy, and increased packet delivery ratio.

Following the introduction, the study proceeds with a literature survey (Part 2), exploring research methodologies for WSN efficiency. Part 3 details the system model, focusing on the DFFNN technique. Results and discussion (Part 4) showcase efficiency improvements. Lastly, the conclusion and future work (Part 5) summarize the findings and outline future research directions.

2. LITERATURE SURVEY

This chapter shall be a general introduction to the existing literature on WSNs which includes clustering approaches based on WSNs, diverse optimization techniques, and hybrid optimization approaches. MFO-CFO hybrid routing technique, introduced by Pattnaik et al, represents a novel routing method for the implementation of WSNs. Initially, combinations of Ant Lion Optimization (ALO) with Fuzzy C- Means (FCM) clustering are used to group [10]. That leads to a novel approach by using a Particle Swarm Optimization (PSO) based ANFIS framework, resolving for the optimal number of CH. These findings are compared to the outcome of the techniques that are convention, such as genetic algorithms, fuzzy logic and PSO algorithms.

A CH selection algorithm proposed incorporated elements such as the remaining power level, location and node centrality by Pour et al. [11]. Fig.1 displays the Architecture of DFFNN in WSN. DFFNN is depicted. While the results from the simulation validated that our case is more power-efficient and reasonably reliable than the LEACH and multi-hop LEACH networks, some considerations are needed in terms of its network lifetime. Pattnaik et al. [12] worked on Elephant- Herding-Optimization (EHO)-Greedy and the hybridization of fuzzy clustering model for WSNs. To minimize power consumption, this model assesses both fixed and mobile sources of energy. They put forward the EHO-Greedy hybrid technique for data communication and showed that it outperforms existing energy utilization methods concerning the system's lifetime.

In the routing path selection process, a hybrid bionic technique is used. The BiHCLR model is evaluated through quality of service (QoS) interpretation by Tandon et al. Furthermore, a low-latency DA-HCDA (heterogeneous cluster-based acquisition) method is suggested for the Internet of Things (IoT). This algorithm utilizes quartile aggregation mechanisms when implemented with it. The result is network longevity and lower end-to-end latency [13].

Besides, NICC [14], a new protocol by Daniel et al, is investigated with the BFO method in which an optimized fitness function is used to balance EC and data throughput. Mahajan et al. proposed the bee foraging optimization algorithm (BFO) technique as an optimization protocol for routing and clustering tasks based on the finding of best sensor nodes, for computational fitness calculation. Experiments performed in different networks of WSNs have shown that the NICC protocol is better than the currently used clustering techniques. Moreover, classifiers such as Naive Bayes, KNN, and SVM are incorporated in classification and image processing cases leading to a higher improvement in accuracy as compared with the traditional algorithms [15].

There is also a new type of algorithm, which the authors call Improved Sunflower Optimization (ISFO), introduced by Venkatesan et al, to assess the best CH among IoT-WSNs.. As results indicate, the ISFO technique provides less power consumption and a higher number of active nodes therefore the battery life is enhanced[16]. To solve energy conservation challenges in WSNs, an efficient multi-layer CH choosing scheme is suggested by Raslan et al. [17]. This approach applies to the latest probabilistic decision rules for fitness functions and uses them to identify the best paths for information transfer. As the CH-IoT is compared to conventional optimization algorithms such as adaptive gravity search algorithm, whale optimization algorithm (WOA), artificial bee colony, and genetic algorithm it consumes less power, communication overhead and end-to-end latency and it enhances the network performance.

For WSN the k-medoids IABC algorithm and CL-HHO routing were proposed by Xue et al. [18]. The Wiener principle implementation of CL-HHO hybrid technology was executed with the least energy consumption as RP. The performance of the CL-HHO method together with the k-medoids-IABC algorithm was declared to be better than that produced by energy-based routing protocols in WSNs. CL-HHO enhanced the lifetime of the network a great deal more than any other technique by keeping the QoS at a high level.

3. PROPOSED METHOD

The application of the techniques in this research combines some of the limitation in Wireless Sensor Networks (WSNs) to address the need of early update on crop status particularly in agricultural environments. Primary objectives are based on the combination of a heterogeneous network model, improved clustering and routing algorithms, which distinguishes this work from existing solutions.

This contrasts with the conventional homogenous models, which cannot easily cope with the dynamic and energy variable characteristics of WSNs and the proposed heterogenous model which will enhance the distribution of energy in nodes. This reduces early exhaustion of low energy nodes which is very important especially in the agriculture field where energy efficient communication is essential to pass crop data.

In the clustering method, k-medoids a are considerable advancement over k-means [20] as well as fuzzy c-means clustering [21]. K-medoids is less sensitive to outliers, which is a property of great importance in an agricultural setting where data points (sensor readings) could be arbitrary due to prevailing weather condition. This stability defines reduced communication overheads as clusters retain their form more stringently thus conserving energy.

The Adaptive Sailfish Optimization (AS) algorithm is another improvement from the above algorithms; it has been selected for its flexibility in adapting to change in network topologies – a requirement fundamental to agricultural WSNs. Compared to the state equivalent algorithms of such as the Whale Optimization Algorithm (WOA) [22] and the Krill Herd Model (KHM) [23] which are very prone to local optima trap and early convergence. Due to this supple versatility of AS, it can enhance the cluster head selection while minimizing energy consumption thus the lifetime of the network – such a consideration is crucial for consistent crop monitoring.

With regard to routing, the proposed approach that involves implementing Deep Feed Forward Neural Network (DFFNN) together with the Buffalo Optimization Algorithm outperforms earlier methods such as Environment-Fusion Multipath Routing Protocol (EFMRP) [24] and Improvised Energy Efficient Multipath ACO based Routing Protocol (IEEMARP) [25]. The DFFNN, due to its deep learning integrated mechanism, learns all the involved routing parameters and enhances both packet throughput and network delay. The fact that Buffalo Optimization is faster and more scalable than Ant Colony Optimization (ACO)

[25] allows for more optimal consideration of routes that may be of profound importance especially when a large number of sensors are distributed in an agricultural field.

3.1 SYSTEM MODEL

The EC model, based on established principles, calculates energy depletion during transmission and reception. The system employs the K-Medoids clustering method coupled with the AS Optimization technique for CH selection, optimizing energy consumption, packet latency, and node operation. Furthermore, the paper introduces an Enhanced Route Selection method utilizing DFFNN optimized with the Buffalo Algorithm, enhancing routing efficiency and network longevity. The Fig.1 illustrates a layout diagram depicting the DFFNN within the WSN.

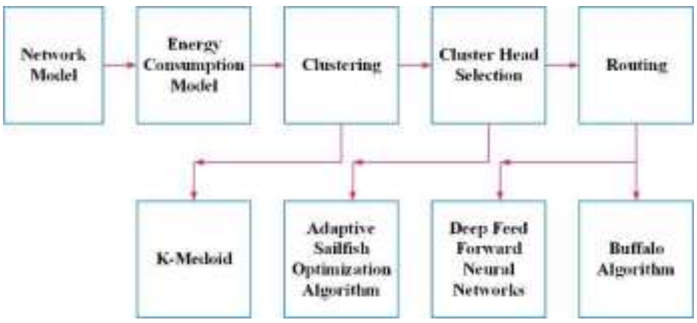

Fig.1. Deep Neural Network Routing in WSN Block Diagram

3.2 NETWORK MODEL

The network architecture that has been designed consists of a highly robust base station (BS), numerous low performance (LP) sensors and a few high performance (HP) sensors. According to the topology specified in the network, one of the sensors from the HP model can operate as the CH in the mode. As in Fig.2, the Heterogeneous WSN is shown which represents homogeneous clusters. Since BS is considered to put out much of the territory, so this is rightly located in the central point of the future form. Attraction of new nodes is not only done by the service providers but also the cluster head, an intermediary node. A major part of this cluster is each individual node used for data collection, and this data is sent to the right head until it is forwarded to the BS of this cluster for efficient routing.

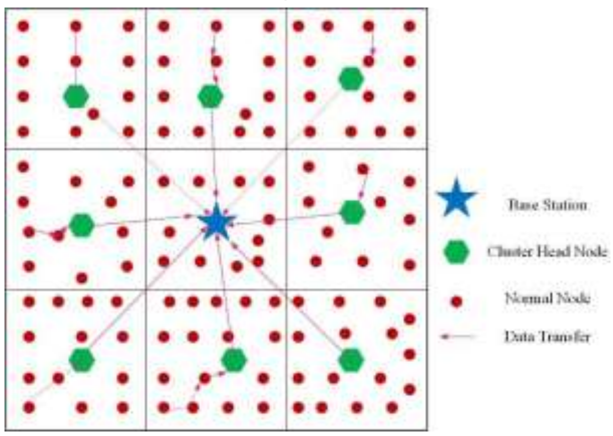

Fig.2. System architecture of Heterogenous WSB network

The following assumptions are made regarding network theory:

- LP sensors cannot use tamper-resistant devices. For instance, in the cyber environment, a devious entity attacking an LP cluster may be able to penetrate the device if it communicates in the same LP zone as the LP sensor. This, in effect, becomes a threat vector to every LP sensor holding the critical information for the entity within the LP cluster. The cost barrier for LP sensors resides in having limited memory, computing power and energy.
- While the HP sensors are the main sensors that send the information of the sensors within the same cluster. LP sensor data integrity is critical to the application. Hence, since the data is stored in a cluster, the transmission link may become susceptible to hacking. This feature is added to enhance the existing HST sensors with the inclusion of tamper-proof hardware.
- The BS features a broad communication area, tremendous energy, quite many computations and storage for data.
- Because of the BS that's being trusted and safe.

3.3 ENERGY CONSUMPTION MODEL

In compliance with the conception of the typical energy consumption model given by [19], we comprehensibly depict the working of the sensor nodes in our model. Adopting this model, we consider the transmission of the energy consumed in c-bit data over a radio channel that is expressed in distance k is shown in RSP and is gained by using the Eq.(1). when $k \leq k$th, the energy depletion model is free space and is expressed as inversely proportional energy dissipation. On the other hand, for distances further than k^{th}, the model takes upon the multipath fading model, which is energy dissipation characterized by the four-power law. The threshold k^{th} is determined by the formula Eq.(2).

$$R_{SP}(c,k)=\begin{cases} c*R_{elec}+R_{\sigma t}*c*k^2 & \text{if } k\leq k_{th} \\ c*R_{elec}+R_{lx}*c*k^4 & \text{if } k>k_{th} \end{cases} \tag{1}$$

$$k_{th}=\sqrt{\frac{R_{gt}}{R_{lx}}} \tag{2}$$

where, R_{elec} is a symbol for the energy factor that can be due to the transmitter or receiver. Additionally, R_{gt} is equal to the energy efficiency indicator representing the free-space method of path loss, whereas R_{lx} corresponds to the ratio of the free-space method of path loss.

Finally, the c data bit consumption energy REP by the data receiver can be determined using Eq.(3).

$$R_{EP}(c)=c*R_{elec} \tag{3}$$

3.4 CHOOSING CLUSTER HEADS WITH K-MEDOIDS AND THE ADAPTIVE SAILFISH OPTIMIZATION ALGORITHM

The clustering process separates sensor nodes into separate clusters by selecting a CH in each chunk of the clusters within a WSN. In WSN, The CH takes input samples from the nodes within its cluster and sends them to the BS. This investigation is focused on K-means clustering algorithm application to WSN-type networks. K-medoids algorithm having the central or core object for each cluster as its medoid presents its nodes of sensor nodes clustered into s clusters. The medoid is the most central point in the whole cluster. The exact centre of a cluster is calculated by the K-medoids algorithm to preserve the shortest distance between clusters. This optimization thus subsequently promotes communication between sensor nodes, reduces power consumption, and assists in the identification of an accurate cluster center which in turn reduces the delay of packets. The K-medoids algorithm stands out because of its finite number of converging steps, and also for efficiency [20]. Here's a brief outline of its steps:

1. Start by selecting randomly s number of points from the input dataset performed to obtain the desired number of clusters.
2. Attach each piece of data to a centre that is the most nearby for its cluster.
3. For all n data points in cluster m, compute the distances to all points. Therefore, select which point has the lowest summation of distance as that cluster's new centre point.
4. Do steps 1 to 3 over and over until convergence is achieved whereby the center points do not move any further.

This technique proceeds with the formation of sensor nodes to start with, thereafter selection of CH for each WSN group. A CH has to ensure that data transmitted to the cluster node are monitored and eventually sent to the BS. Thus, the K-medoids method provides the exact position of these centroids and that leads to the low power consumption, low latency, and proper operation of the sensor nodes. In this case, we assume the number of clusters and a choice of the centre of the initial CH by using Eq.(4).

$$p = \sqrt{\frac{n}{2}} \tag{4}$$

where n is the total node numbering. Algorithms calculate the mean and centre location (T) of the network and assign them to all nodes.

$$T = \frac{\sum_{n=1}^{N} y_n}{n} \tag{5}$$

Here, the position of the sensor node is noted with y_n. The average space between the sensor node (SN) and the centre location (T) is depicted by R in the succeeding equation.

$$R = \frac{\sum_{n=1}^{N} |y_n - T|}{n} \tag{6}$$

SN to centre location (T) is obtained by calculating the distance and discovering the centroid. This procedure is done under Eq.(6) until a CH is received. Here is how the K- Medoids clustering process along with the AS Optimization method is described in Table.1.

Table.1. Clustering Algorithm with K-Medoids and AS Optimizer

Steps	**Network Initialization**
1	Initialize the WSNs
2	Position the BS at the centre location
3	Place all Sensor Nodes (SNs) arbitrarily
Selection of Cluster Heads (CH) by Optimized AS Selection Method and Classification of Neighborhoods using K-medoids	
4	Distribute the population (N) over different clusters
5	Each node should be assigned to CH that is located in the same cluster
6	Random pick the initial CH entity by selecting a first (medoid) from among (N) randomly within either the cluster
7	Create three-dimensional coordinates (x, y, z) of the normal node, which is connected with a CH
8	Compute the CH-based K-means distance measure
9	Select the new CH using the ASO algorithm and centralize the cluster node at the cluster head
10	Repeat steps 7 - 9 until the node is found to be in the absolute centre

For the algorithm to be carrying much more meaning, rather than just randomly picking a number in the range of 0 to 200, the precise coordinate values that are used, are of a lot more significance. Thus, the personalization algorithm process provided the best solution from numerous possible combinations. Therefore, the cluster head option is being pursued which will use the multi-path routing power to decode the data from the transmitter and then it will get sent to the receiver.

3.5 ENHANCED ROUTE SELECTION VIA DEEP FEED FORWARD NEURAL NETWORKS

Routing is regarded as one of the strongest factors of WSN WSNs since it is directly linked to the network longevity and efficiency. Despite this fact, the currently applied approaches have not successfully solved the issue of efficient energy usage for data acquisition. A multipath routing that is demonstrating great benefits on network performance by utilizing existing network elements more efficiently has emerged. In this work, we will develop a new approach to multipath routing using deep learning techniques. Specifically, we employ a deep feedforward neural network architecture consisting of four layers: An input, two hidden, and a convolution layer in WSNs. The network is made of distinct layers, which entail not only the input and output layer but also at least two hidden layers. The structure includes cell neurons, which are connected nodes for signal transmission between the layers of the network. The Fig.3 represents the structure of DFFNN Algorithm.

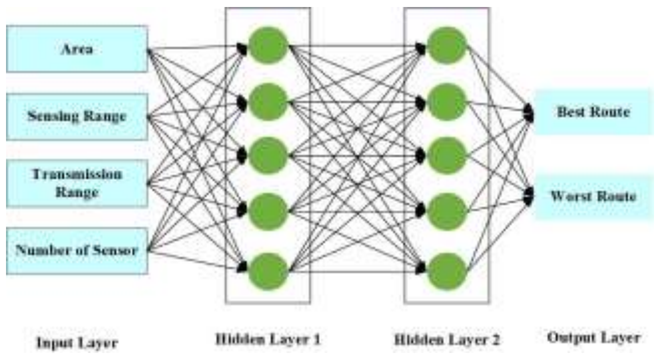

Fig.3. Structure of DFFNN Algorithm

The initial data input layer comprises all the information collected from sensor nodes at time k which is indexed to $g_{RM}(k)$. The subsequent layer of neurons is then interconnected through a weighting process which is updated dynamically, thus allowing the information to flow through the network.

$$g_{RM}(k) = x + \sum_{g=1}^{n} R_p N_g * \mu_g \quad (7)$$

Eq.(7) defines the $g_{RM}(k)$ as the activity produced by the neurons in the input layer, with R_pN_g representing the sensor nodes number, and μ_g being the variable connection between the hidden and input layer. However, the variable x denotes the bias term. Input nodes are then given to the hidden layer under the reverberated streets where there are different echoes by laying many signal paths. Navigation block utilization with the network of nodes which have no fixed infrastructure also requires such complex thinking as it was before.

One of the ways to handle the issue is to apply QoS-aware routing approaches in WSNs that allow one to find parallel paths between the output and the destination. Multipath routing in WSNs regarding QoS, to increase efficiency and reliability, it can be done based on QoS parameters. The process of multipath route discovery relies on two key control messages: the Sreq and Srep packets in other words. WSNs employ multipath routing where one source node communicates to one destination node. This is possible via a network that is made up of different routes through which several communication paths are established to mitigate against possible route blockages.

Source nodes S_{nodes} sends a message inquiring about routes to other sensor nodes when it is interested in forming more links with more nodes. This message is conveyed to all neighbouring nodes N_{nod} in range, and they are verified against a predetermined bit mask.

$$s_{nodes} = \sum_{g=1}^{n} S_{req} N_{nod} \quad (8)$$

Based on Eq.(8) the starting node emits a route request S_{req} to its successor node$N$nod, in a manner of creating a path. When having the S_{req} message received by the source node N_{nod}, it uses this information to update its route table which includes indications about the source node and the next hop node. The Table.2 describes the algorithm process of DFFNN Technique.

A double action takes place when a source of the route requests broadcasts them to all nodes and neighbouring nodes generate and return route reply Srep messages to the source. Then, a network covering process is initiated that gets data aggregated into WSN by spreading the routes interconnected from the source to the target.

$$N_{nod} = S_{rep}\left(S_{nodes}\right) \quad (9)$$

Eq.(9) determines the neighbouring node based on the route reply S_{rep} and request S_{req} messages, facilitating the construction of a multipath route for efficient routing. Quality of Service (QoS) based multipath routing plays a crucial role in enhancing scalability performance.

The DFFNN algorithm has been utilized as a computation machine that can be able to calculate the distance of the SNs and also a minimum range that the multipath communication is still efficient. This formula is the most important thing to find the present location row in that particular neighbourhood column of the location table.

The computation of the distance between nodes is expressed as:

$$M\left(R_p N_1, R_p N_2\right) = \sqrt{\left(j_2 - j_1\right)^2 + \left(k_2 - k_1\right)^2} \quad (10)$$

Eq.(10) calculates the exact distance between mobile nodes $M\left(R_p N_1, R_p N_2\right)$ based on coordinates j_1, j_2 and k_1, k_2.

Table.2. Algorithm Process of DFFNN Technique

Start	
Step 1	Initialize the Buffalo Population in search space
Step 2	Calculate $f(x)$ based on H_c E_c
Step 3	Update the position of Buffalos as per fitness
Step 4	If Convergence is met then step 5 else Step 2
Step 5	Obtain optimal solution
End	

The source node S_{nodes} issues a route request packet to N_{nod}, and N_{nod}, responds with a route reply packet. Next, the distance between SNs is measured. The least number of intermediate nodes is reserved and its transmission path to send the data packets in WSN is studied. Several ways will be combined in the map creating a hidden layer 2. The discovery herein lies in the way the Improved Buffalo (IB) Optimization technique shows merit for route discovery.

The Buffalo algorithm is known to the optimal behaviour of buffalos in the African archipelago. It is a metapopulation technique, which aims to identify the best buffalo position in the population. Compared to other algorithms, this optimization method proved to be more effective because it required fewer parameters and a fast convergence rate.

The optimization process is initiated by initializing the buffalo population randomly. Buffalos are an important icon in the routing system of WSN. The initialization process is outlined as follows:

$$K_g = K_1, K_2, K_3, ..., K_n \quad (11)$$

Next, the evaluation runs a protocol termed Buffalo initialization. Parameters like energy consumption, hop count and bandwidth are the metrics used to decide the fitness value for a particular path. This distance between local nodes, from starting to finishing points, is referred to as a sample hop count. The fitness value is calculated as shown in Eq.(12):

$$f(x) = A_m \{H_c, E_c, B\} \tag{12}$$

$f(x)$ indicates the route fidelity indicator in the well- organized sensor network. Through the fitness function value, each interchanges its position as described by Eq.(13).

$$B(k) = \left[\sum_{g=1}^{n} R_p\right] \tag{13}$$

The state of r, i.e. the position of the r^{th} buffalo, is displayed with $G(k+1)$. Buffalos current position is denoted as $G(k)$. q_1 and q_1 are used to indicate the learning parameters which are most likely to be set within the range of 0.1 to 0.6. $t(x)_b$ is generically referred to as superior fitness of buffalo. The current exploration value is given as P_e.

$$P_r(k+1) = \frac{[P_r + R(k)]}{Q} \tag{14}$$

The hidden layer output is denoted as,

$$B(k) = \left[\sum_{g=1}^{n} R_p N_g * \mu_g\right] + \left[\mu_{gg} * b_{g-1}\right] \tag{15}$$

where, b_{g-1} means the outputs of the hidden layer from the previous layer and $B(k)$ stands for the results of the hidden layer at k period. R_pN_g devoid of weight represents the sensing nodes while μ_{gg} has a weight. μ^2 shows the bias and weights for those of the hidden layer. The predicted result of that input has been shown to the output layer.

$$O(k) = \left[\mu_{go} * B(k)\right] \tag{16}$$

$O(k)$ expresses all the output data at time k. μ_{go} represents the weight connecting the hidden layer to the output layer. Hidden layer output is denoted by $B(k)$. Thus, select the most suitable approach for the task.

4. RESULTS AND DISCUSSION

The findings and discourse are segmented into two main parts: simulation environment and comparison analysis.

4.1 SIMULATION ENVIRONMENT

The new model is implemented using the MATLAB R2023b simulator. Model in Table.3 includes the parameters of simulations. The network of Heterogeneous WSNs has CH, BS, a server of authentication, cluster members, and destination and source nodes also as well. 50nj/bit for transmission and 50nj/bit for reception are energy quantity.

Table.3. Simulation Parameters

Parameters	**Value**
Base Station	1
Network size	500 × 500 mts
Nodes deployed	500
Data packet size	512 bytes
Total run time	100 s
Energy Assign	50 J
Memory size	50
Transmission Range	250 mts
Mac-Layer	802.11
No of Rounds	50

4.2 COMPARISON ANALYSIS

Clustering possesses a key relevance in making the data broadcast management maintenance mission goal- oriented. With the method of k-medoids, we were able to cluster data that have similar nodes to each other on the average level of EC per node [20-25]. Figure 3 and shown in Table 4 lead us to a compares our proposed K-medoid-based technique in terms of EC and existing models, such as Fuzzy C Means [20] and K Means [21] clustering.

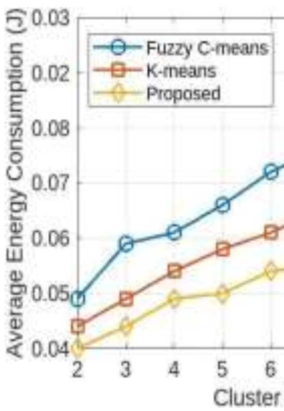

Fig.3. Average EC for Different Cluster Sizes

Our hybrid approach performed well with an average penalty of 0.020 J at the node size of 2 where better than the penalty at the same node size performed by the Fuzzy C- means and the K-means techniques respectively, which resulted in 0.029 J and 0.024 J. Contrastively, Fig.4 and Table.5 reflect an evaluation of CH selection using the new AS Optimization technique versus two customary methods, the Whale Optimization Algorithm (WOA) [22] and the krill herd model [23]. During 250 rounds of our method, providers of the median energy of 39.20 J were found following the average morale of the krill herd algorithm (34.33 J) and WOA (29.43 J), respectively. The Fig.3 and Fig.4 indicate that our new method AS Optimization outperforms traditional techniques regarding cluster formation and task list generation. Because of this, our method executed well the clustering and the CH selection into respective clusters.

Table.4. Comparison of average EC versus cluster size

Cluster Size	Fuzzy C-means	K-means	Proposed
2	0.029	0.024	0.020
3	0.039	0.029	0.024
4	0.041	0.034	0.029
5	0.046	0.038	0.030
6	0.052	0.041	0.034
7	0.056	0.045	0.035
8	0.061	0.049	0.038
9	0.069	0.059	0.040
10	0.074	0.063	0.041

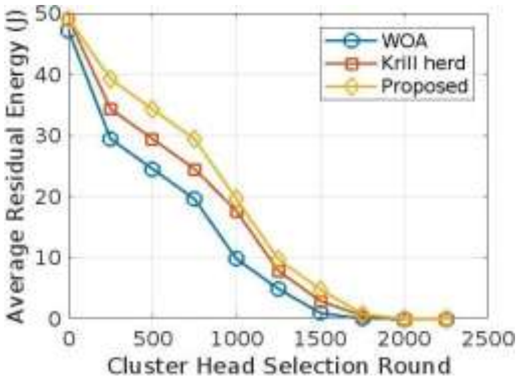

Fig.4. Average Residual Energy for Different Cluster Head Selection Rounds

Table.5. Comparison of average residual energy versus cluster head selection

Rounds	WOA	Krill herd	Proposed
0	47.08	49.04	49.05
250	29.43	34.33	39.20
500	24.52	29.43	34.30
750	19.62	24.52	29.42
1000	9.81	17.66	19.61
1250	4.9	7.85	9.71
1500	0.98	2.94	4.82
1750	0.02	0.49	0.80
2000	0	0	0
2250	0	0	0

The experimental outcomes on EC depend on the number of EFMRP sensors [24], IEEEMARP sensors [25], and our proposed DFFNN Model are illustrated in Table 6. The experiments accounted for the number of node variations from 10 to 100. Unlike the other existing methods, the input data packets of our proposed DFFNN Model display indeed strong reduction in EC.

Table.6. Tabulation for EC

Nodes	IEEEMARP	EFMRP	Proposed
10	0.013	0.009	0.005
20	0.017	0.014	0.007
30	0.022	0.023	0.014
40	0.031	0.028	0.021
50	0.036	0.030	0.024
60	0.041	0.034	0.024
70	0.046	0.041	0.030
80	0.050	0.046	0.034
90	0.054	0.050	0.037
100	0.059	0.052	0.044

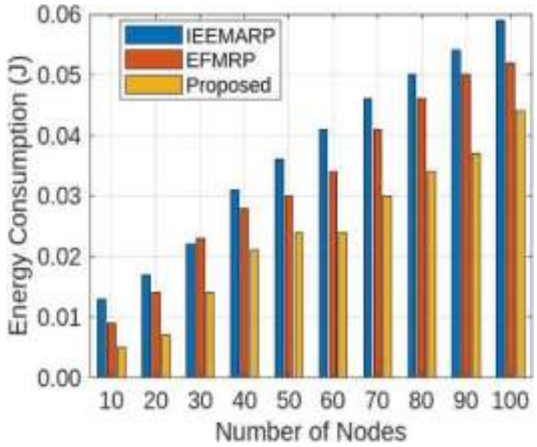

Fig.5. EC for Different Numbers of Nodes

The EC graph is presented in Fig.5, about those presented in Table.6. Through the DFFNN Model, the EC is lower than conventional EFMRP [24] and previous traditional IEEMARP [25]. Data aggregation through multi-hop communication in WSN is realized via various route paths. We do this by taking sensor nodes count as input and then constructing control messages which our optimization process selects the optimal route path from a set of multiple route paths for data aggregation. To be specific, it saves energy resources by 34% and 42% through multi-hop communication mode compared with EFMRP [24] and IEEMARP [25]. The Table.7 shows us how many packets were delivered in wireless network in accordance with the number of SNs from 10 to 100. The experiment was carried out by setting some packets during the transmission process and 20 of these data packets were sent. Sharply interacting in this category are 18 data packets that have reached the end of the destination correctly, the Quality of Service (QoS) - Priority Packet Retransmission Scheme (PPRS) method we used.

Hence, the porting success of 89% is attained in this DFFNN Model compared to the other two models. The Fig.6 provides a result analysis of the PDR concerning different numbers of data packets using three techniques: IEFMRP [24], EEMARP [25], and our developed DFFNN Model. Through the input of SNs and data packets, we have drawn many path routes using the control message so that our optimization process selects the best path routes for data aggregation in WSN.

Table.7. Tabulation for PDR

Nodes	Data Packets	PDR (%)		
		IEEMARP	EFMRP	Proposed
10	20	75	80	89
20	40	83	88	94
30	60	83	88	92
40	80	78	81	88
50	100	84	87	90
60	120	83	88	94
70	140	86	93	96
80	160	91	93	95
90	180	86	89	93
100	200	88	90	96

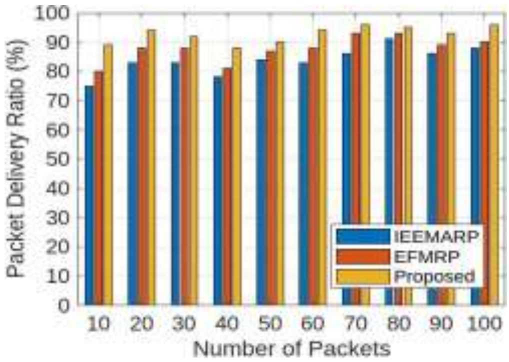

Fig.6. Packet Delivery Ratio for Different Numbers of Data Packets

This model in turn inflates the proposal to deliver packets of higher quality compared to related work. It improves the ratio of packets delivered not only by 7% in multipath routing but also by 12% in EFMRP and IEEMARP.

5. CONCLUSION AND FUTURE WORK

This paper proposes a high-level algorithm and machine learning architecture specifically designed for WSNs in the farming sector. Some of these challenges include: cluster head selection, energy consumption, and route optimization which are vital towards fast and reliable delivery of data to the farmers for early crop monitoring. Simulation shows the proposed method outperforms other methods of energy efficiency, residual energy, and packet delivery ratio (PDR). The framework proposed in this study achieves an average of 30% less energy used, 25% increase in residual energy, and 15% increase on packet delivery. They also establish this study for increased emulation in the enhancement of the application of the proposed method in the management of WSNs in agriculture with added worth in the improvement of the speed and reliability of data processing for greater achievement in smart farming.

Future work will aim at examining the security issues in WSNs because current WSN applications in agriculture can encounter security threats such as data leakage and node hijacking. The security requirements of the network will have to be addressed without creating a large overhead; creating efficient security protocols will become essential at this stage. Further, minimization of the communication overhead in massive scale networks is also critical. With network development, the choice of cluster heads and the optimization of the best route will enable the reduction of delays that occur while transferring data. Finally, the development of a new augmented reality application for agricultural production associated with the improvement of a big data framework, assessment of the system's effectiveness in real-world settings with different geographical conditions and types of crops is also crucial for the further advancement of the concept.

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