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A Machine Learning-Based Optimization Algorithm For Wearable Wireless Sensor Networks

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Abstract: In an Internet of Things (IoT) setting, a Wireless Sensor Network (WSN) effectively collects and transmits data. Using the distributed characteristics of the network, machine learning techniques may reduce data transmission speeds. This paper offers a unique cluster-based data-gathering approach using the Machine Learning-based Optimization Algorithm for WSN (MLOA-WSN) designed in this article for assessing networks depending on power, latency, height, and length. Using the cluster head, the data-gathering technique is put into action, with the data collected from comparable groups transmitted to the mobile sink, where machine learning methods are then applied for routing and data optimization. As a result of the time-distributed transmission period, each node across the cluster can begin sensing and sending data again to the cluster head. The cluster-head node performs data fusion, aggregation, and compression, which sends the generated statistics to the base station. Consequently, the suggested strategy yields promising outcomes as it considerably improves network performance and minimizes packet loss due to a reduced number of aggregating procedures. The existing method for findings of the MLOA-WSN system is a value of 2.43, a packet loss rate analysis of 7.6 and an Average delay analysis of the optimizers for 224. The method was evaluated under various settings, and the outcomes indicated that the suggested algorithm outperformed previous techniques in terms of decreased delay and solution precision.

Keywords: Wireless Sensor Network, Data Transmission, Machine Learning, Internet of Things, Optimisation Algorithm, Cluster head.

1. INTRODUCTION

The architecture of a WSN is based on many tiny Sensor Nodes (SNs) that may detect location-specific information by working with other nodes and transferring the data to the Base Stations (BSs) of the particular location [1]. WSN is a collection of SNs partitioned in a specified place that, depending on the applications, operate concurrently to achieve a specific goal. WSN is a significant technology used in several applications, including traffic management, automation, medical services, and environmental monitoring. WSN aims to verify the dependability and effectiveness of the packages while sending the SN to the base station. SN comprises a battery that delivers minimal energy and a power source. The SN ceases to operate if all its energy is removed. As specific nodes are unplugged from the sink, the WSN is eventually disassembled. Consequently, conserving energy and extending the lifespan of SNs are the most critical objectives, which must be supported with data transfer for long-term recovery. Several strategies for creating WSNs are based on diverse topologies. Classical mesh architecture requires routing databases for packet routing since it is complex and requires more maintenance and information exchange, increasing energy consumption [2].

In addition, updated routing databases might cause packets to establish a loop between nodes. The simplest method for routing packets is created by tree topology. It is resilient against node loss and less likely for packets to be routed in loops. Grouping in WSN is optimized for data aggregation and reducing the number of nodes for data transport to the sink [3]. Typically, grouping is created by dividing the network into clusters comprised of cluster heads (CH) and

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participant nodes. CH gets data from the membership nodes since member nodes do not transmit data straight to BS, and CH is chosen based on specific criteria. The CH is responsible for gathering data from different member nodes and delivering it to the BS. The grouping has two stages: the initialization phase and the steady-state stage. In the first set stage, the CH is picked based on the required proportion of CH and the incidence of nodes that have that chosen CH. As CH, a random number in the range [0, 1] is selected, and each node strives to acquire its position. During the steady-state stage, the interchange of data among the CH and the membership nodes is based on a single-hop method, and all CH combine the acquired data and communicate it to the BS. The multipath approach is an alternative way of sending information from the CH to the BS via several transmission routes. Multiple pathways use charges at a similar rate to increase the network's lifespan and achieve load balancing. Multipath routing is an upgraded approach for boosting transmission reliability and fault tolerance [4].

WSN offers a balance between energy usage and transmission latency. Therefore, multipath routing is an effective method that should be explored for enhancing bandwidth and fault tolerance in WSNs. Multipath routing may remove the necessity of upgrading lines, optimize bandwidth allocation, optimize the data transmitting rate, and increase the reserved power of SN. Due to the diversity of its design algorithms, a WSN optimization approach compels academics to focus more on optimization. Static and dynamic optimization methods are used in WSN. Static optimization optimizes the WSN just after deployment and keeps it stagnant throughout the network's lifespan. Static optimization techniques are content with steady or predictable workloads but are not adaptable to changing application needs or external stimuli. Because it can adjust to new applications and real-world conditions, dynamic optimization can optimize WSNs on the fly while they're running stimulus needs. It has been used in several applications, including the design of mechanical devices, neural systems, information exchange, and image processing [41-46]. To reduce energy waste and prolong the life of WSNs, the CH must be selected appropriately. The selection of CH is seen as an optimization issue. The scholars use the Particle Swarm Optimization (PSO) technique to choose CH [47-51]. PSO is simple to implement and provides global search, the ability to avoid local maxima, and quick convergence for the best solution.

WSN networks encounter notable obstacles, such as substantial energy consumption, latency problems, and data integrity concerns. These difficulties arise from the networks' restricted battery life, the need for prompt data delivery, and the imperative for dependable data transfer. Furthermore, wearable wireless sensor networks (WSNs) must handle intricate scalability effectively, interference caused by numerous wireless networks, and the capacity to adjust to changing circumstances, such as node movement and fluctuating data loads. Conventional optimization techniques have difficulties in properly tackling these dynamic problems. This work aims to create a machine learning-driven optimization algorithm specifically designed for wearable wireless sensor networks (WSNs). The system intends to enhance energy efficiency, minimize latency, improve data integrity, and increase scalability and flexibility. The suggested method would enhance the performance of wearable wireless sensor networks (WSNs) by resolving important concerns. This improvement will increase the dependability and usefulness of these networks in real-world situations. The difficult challenge is to build methods for effectively handling various circumstances. Major concerns such as fault detection, dependability, security, grouping, aggregating, time management, relocation, and power-saving routing must be explicitly addressed. Machine Learning (ML) enables automated learning, enhances the experience, and generates algorithms to retrieve information and learn independently.

ML plays a crucial role in several WSN applications because (i) WSN often notices changes in surroundings, and (ii) WSN even gathers data from inaccessible regions (iii) As WSN is implemented in complex applications, it is challenging to give an adequate theoretical framework for describing platform behaviour (iv). Network builders find evaluating the correlations between copious amounts of network information challenging. [5]

The primary contributions of this article are shown below:

- Designing a unique cluster-based data-gathering approach using the Machine Learning-based Optimization Algorithm for WSN (MLOA-WSN) to assess network power, latency, and delay.
- A multi-objective male lion optimization method was used to optimize the WSN parameters.
- Analyzing the Artificial Bee Colony (ABC) optimization obtains better routing and network issues.
- The simulation outcomes are verified based on metrics such as packet loss rate analysis and an average delay analysis compared with the existing machine-learning models.

The remainder of the article is organized in the following manner: section 2 indicates the background of the optimization algorithm for WSN. The proposed Machine Learning-based Optimization Algorithm for WSN (MLOA-WSN) is designed and analyzed in section 3. Section 4 indicates the software outcomes and the performance outcomes. The conclusion and future scope are shown in section 5.

2. LITERATURE REVIEW

This section offers a short literature review on data gathering and grouping strategies using ML algorithms in wireless sensing networks. This paper presents a method for transmitting data via many paths in WSN by introducing a unique, optimized method, dubbed Exponential Cat Swarm Optimization (ECSO), which combines the exponentially weighted arithmetic mean and Cat Swarm Optimization (CSO) [6] lonies Optimization (PFACO) approach, which combines the fuzzy and Penguin Searching Optimization

Algorithms (PSOA). After selecting the optimum CH, the suggested ECSO method performs multipath transmissions.

This study employs if-then methods using fuzzy logic to choose the cluster leader according to specific fuzzy characteristics [7]. Particle swarm optimization was used to enhance the ranges of the fuzzy affiliation functions to improve them. In addition, recent research has demonstrated that the addition of mobile collectors to a system that gathers data over short-range networks also helps to save a lot of power. For this study, we divide the system into clusters and use a mobile emitter to go from base stations or static sinks to the chosen clusters leadership in each cluster, gathering information during a single hop.

Scholars developed the WSN integration system to focus on the latency and power trade-off as opposed to the New Optimum Sleep Schedule (NOSS) scheme offered for energy and dependability optimization [8]; it has three operational purposes: (i) A preferentially optimized data forward technique is utilized to forward the collected data preferentially, thereby maximizing the data dependability, and (ii) an enhanced fish clustering optimizer method is employed to calculate the state of each sensing node, whether it is awake or sleeping, therefore reducing energy consumption usage. (iii) A partly making choices according to priorities method is utilized to determine which of several user queries is the best.

This paper proposes a method based on grid segmentation and flexible reinforcement learning to optimize network lifespan and energy-efficient information aggregating for dispersed WSN [9]. Grid grouping is first used for cluster creation and CH collection. In addition, a flexible reinforcement learning approach based on rule systems is utilized to choose the data aggregator node depending on criteria like distance, community overlapping, and algebraic connectedness. The mobile sinks are relocated dynamically inside a grid-based clustering network area using a fruit fly optimization approach.

This study proposes an efficient Particle-Based Spider Monkey Optimization (P-SMO) method for selecting the ideal path to manage secured communications in WSN [10]. In this manner, the system is replicated, and the cluster centers are chosen based on the Effective Educational Automata-Based Cell Clustering Method (ELACCM) such that the guided route is built based on the selected CHs. Consequently, the suggested method computes the safe routing route based on criteria like energy, latency, consistency component, and trust.

This work provides a method for achieving optimum sensor resource use by compressing and aggregating raw data [11]. The idea is to eliminate this duplication by deleting a fixed number of data packages and retaining the most significant and relevant ones for rebuilding. Data processing stopped a particular sensor data packet, resulting in a low connection speed and a reduced probability of packet collisions over the wireless channel. Image compression removes redundant storage of collected data to decrease the resource utilization of wireless sensor nodes, resulting in storage savings and the transmission of just a tiny data stream within the connection capacity.

[12] proposes a trust-aware, condensed sensing-based data acquisition and routing method for clustering WSN. Compressed detection is employed to aggregate sensor node data with little overhead. Using the artificial bee colony method, ant colony optimization, evolutionary algorithms, the firefly method, and particle swarm optimization, a trade-off between the data transmission, hop count, the quantity of sent messages, and the most trusted route has been obtained.

The innovation in this study is using the Grey Wolf Optimization (GWO) method to choose energy-saving group leaders [13]. Although this strategy is well-liked by academics for its hunting style and strong leadership qualities, it fails to provide satisfactory outcomes when used for research and exploitation, leading to subpar grouping in WSNs. The proposed method includes a tuning variable for efficient search and exploitation, which is then utilized to address the WSN-related problem.

The research suggests a topology-optimizing and an incremental variable recognition approach for predicting the commonly applied components in WSN to reduce energy usage and data volume [14]. Using this method, a society's distributed structure may be enhanced to the point where all its leaf nodes can establish direct connections to the controller node. In a circular architecture, the far-leaf nodes may reduce connectivity and energy usage by connecting to the head node via two nearby relay nodes. Based on the optimal topologies, an incremental identifying approach is presented to optimize the informational capability by conveying treated results instead of raw data, reducing the data required for computation and storage. This paper provides a Resource Secure-Aware Router (RSAR) method that can be implemented [15]. The RSAR begins with the determination of the sensor node's trust system. Then, the numbers are computed using the optimization method for unconditional tug-of-war and optimal trust inference framework. The data gathering aids in decreasing the immediate information flow of the intermediate element to bypass unnecessary steps and focus on the essential info, sending the aggregated data to the receiver end.

Based on the survey, there are several issues with existing models in attaining a high packet delivery ratio, network performance, reduced latency, delay, and energy consumption. WSNs are susceptible to various attacks, including blocking, tampering and espionage. The network's security and the data it gathers is a critical issue. WSNs are often utilized in areas with high interference levels from other wireless devices. Many variables limit the practical optimization of wireless sensor networks, including network connection, delay, reliability, coverage, structure, cost, and

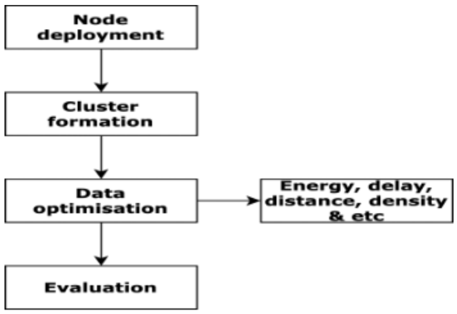

Figure 1. (a) System model of optimization method for MLOA-WSN

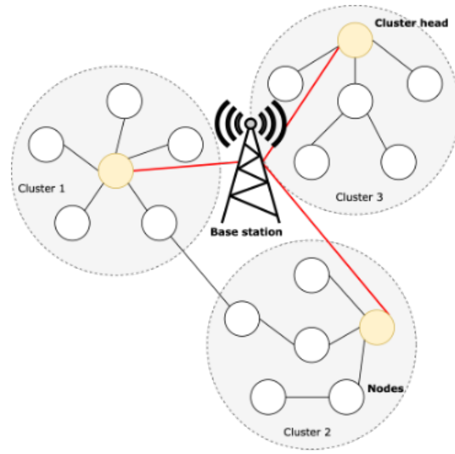

Figure 2. Architecture of the nodes that are operating inside the WSN environment.

latency, among other benefits and interference, all have a role. Developing or selecting a novel software package to evaluate the functionality of wireless sensor nodes is no easy task; there are many factors to consider, including but not limited to processing power constraints, rising sensor node density, unreliability, and limited processing resources. Sensor prices vary according to their capabilities and complexity. The size and cost limits result in resource constraints like energy, processing speed, memory, and bandwidth. Therefore, an improved multi-objective optimization model is required to optimize several network factors such as power, latency, lifespan, throughput, and routing. To do this, this study proposes the MLOA-WSN model in the following section.

3. PROPOSED METHOD

A. Machine Learning-based Optimization Algorithm for WSN

The network-deployable nodes form the group, followed by the choice of the cluster head. Each cluster has N members that create multiple data packets with a defined size. Each cluster may broadcast data, ordered by aggregation, to the ground station. The network is improved by implementing data acquisition with a multi-objective male lion optimizing method and analyzing efficiency indicators.

Fig. 1 depicts the multi-objective optimization approach of the MLOA-WSN. The node deployment is done in WSN. After cluster construction, data optimization and assessment are carried out. This research applies multiple data optimization targets in a WSN context. The Bare Metal service prepares a node for use by a workload by performing node deployment. As previously stated, the cluster formation process is statistical. As a result, clusters of a specified size are never generated during the cluster production process. The process by which businesses collect, analyze, and store data for optimal efficiency is known as data optimization. To avoid energy depletion in sensor nodes, it is necessary to investigate the energy management problem in WSN.

B. Data aggregation

While transmitting voluminous data to the sink directly, WSNs encounter difficulties and suffers losses. The issue is efficiently resolved by aggregating data. Data from nearby sensors are gathered during aggregating, and depending on the grouping strategy, an aggregating node is chosen. The efficiency of the aggregation procedure is then determined by the transmission of fused data to the Base Station (BS) via a suitable routing algorithm. There are three types of WSN nodes regarding aggregating: nodes that detect, aggregate, and answer questions. When gathering data from several sensor nodes, the aggregation site node uses operations including highest, lowest, count, and average, which are then communicated to the mobile sink. Duplication is reduced here, extending the network's lifespan and lowering the number of packet transmissions. Due to the aggregating procedure, the number of packages and conflicts is substantially reduced, along with the number of retransmissions, which reduces energy use and computing time and increases the network's performance.

Fig. 2 depicts how each group interacts with one another with the assistance of the cluster leader. The data are taken from the smart sensor WSN Kaggle Dataset [22-26]. The cluster head consolidates the information before reaching the ground station. Thus, the cluster is built based on sensing node data similarities. As only groups of comparable data need data acquisition, the machine-learning system estimates data similarities between the nearest neighbors after the nodes are installed. Typically, disparate data groups transfer data to CH, sending the information to the sink node. Information collected from clusters with comparable characteristics is transferred to the sink node. Due to the decreased number of aggregating operations, network performance may be maximized, and packet loss can be reduced.

C. A male lion optimization system based on many objectives.

The theoretical concept of the lion optimizing method is reasoning from the lion's actions characteristics, such as hunting, wandering, migrating towards a safer area, mating, immigration, defence, population balance, and convergence [16]. These collaboration qualities are theoretically mod-

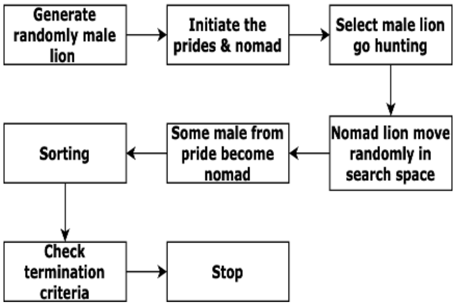

Figure 3. The workflow of the activation of the WSN

elled to develop an appropriate optimization technique. The beginning population is determined by a random solution called "lions." The optimal answer found during earlier rounds is the spot where each lion spends the most time, which is altered progressively during the optimizing cycle.

The workflow of the WSN deployment is shown in Fig. 3. The pride region comprises the best places each participant has visited. Young lions are isolated from parental pride and become nomads when sexually mature, yet they lack the authority of typical men. The nomadic lion randomly explores the search space to locate a more secure option. The residing male will be kicked out of the pride and transformed into a nomad if the dominant nomadic males enter them. Due to conditions such as food scarcity and fighting, the weakest lion will perish. This procedure is iterative until all terminating conditions are satisfied and all male lion optimizing methods reach the optimal solution.

Algorithm of MLOA-WSN deployment phases include:
Step 1. Create the randomized male lion community.
Step 2. Introduce the pride and nomadic lions.
Step 2.1 A randomly chosen nomad community will divide lions into P (number of pride) and establish territories for each pride.
Step 3. Do one thing for each pride.
Step 3.1. Randomly choose lionesses that hunt.
Step 3.2. The surviving lions in the pride move to one of the better position's "n" in the territory.
Step 3.3. In a population survey, the wandering proportion of the area is picked and verified randomly for each male.
Step 3.4. A weak male lion is expelled from his pride and branded as a wanderer.
Step 4. For Nomad, perform.
Step 4.1 A nomadic lion roams space at random in search of food.
Step 4.2 Pride unexpectedly attacked a male lion.
Step 5. Perform for each pride.
Step 5.1. A guy from the pride transforms into a wanderer.
Step 6. Perform.
Step 6.1. Nomadic lions are ranked by their fitness score.
Step 6.2. A wandering lion's fitness level determines whether it survives not.
Step 7. If the termination is not fulfilled, go to step 3.

The male lion algorithm strikes a decent mix between discovering new solutions and making use of existing ones that are already out there. This equilibrium prevents the algorithm from settling into a local optimum configuration and guarantees it can discover the best routing pathways and clustering configurations. Because of its adaptive search mechanism, the male lio optimization algorithm can handle changes in its environment, including the mobility of nodes and fluctuations in signal intensity. Network performance in ever-changing WWSN settings relies on this resilience [27-30]. The male lio optimization method lowers sensor node power consumption by improving cluster formation and data aggregation. By reducing the amount of long-distance transmissions, efficient clustering helps to save energy.

D. ABC-Based Routing Technique

The ABC paradigm's novel heuristic approach was inspired by bee colony foraging arrangements [17]. The ABC method divides a "colony" into three distinct "bee" groups: observers, scouts, and engaged bees. The technique finds the best path by analyzing the number of bees, each representing a location in a search area. A worker bee is an occupation bee if it returns to a food source it has already visited, a scout bee if it investigates randomly, and an observation bee if it waits in the "dancing" region to choose a food source. The quantity of "nectars" of food providers stands for a solution's quality (suitability), and the location of food supplies signifies practical answers to difficulties. The worker bees make up the lower half of the colony, while the spectator bees make up the upper half. The ABC method has four key steps: startup, population updating, bee source choice, and population removal. For parameter introduction, the Oppositional-Based Learner (OBL) approach is used to increase the convergence rate of the ABC method [31-35]. After calculating the cluster's evolution, there is a great need for an improved routing strategy. To resolve the energy degradation issue with fewer hops, a particular routing model must transfer data from stations to CHs and then to the Master Stations (MS).

By iteratively searching for solutions, the ABC algorithm can adapt to changing network circumstances in real-time, such as the energy levels and mobility of nodes. Because wearable WSNs operate in constantly changing environments, this flexibility is vital for preserving effective data transmission pathways. Distributing data transmission positions across nodes is an intrinsic feature of the ABC algorithm that helps to balance the load. The total lifespan of the network is increased since this load balancing stops certain nodes from running out of power too soon.

E. Initialization stage

The node's food supplies are acquired. These responses about specific geographic applicability for food supply development are arbitrarily recorded. It is represented as $Z_{(y,l)} = \{z_{y1}, z_{y2}, \cdots, z_{yL}\}$ with r ranging from 0 to 1.

F. Employed bee stage

The optimum fitness score for the created answer has been achieved by utilizing the Employed Bee. When sending specific data to MS, data transmission occurs on all CHs. The CH transmits the "path message" to fulfill the nodes located between two levels. The "path message" consists of the Node ID, Precipitant power, Width of Queue, and the likelihood of a route. CH stores the crucial information in a table designated as the Relay Table. GHh_x then installs relay gathering SR_g and selects relay g, which is stated in Equation (1).

$$\mathrm{SR}_{\mathrm{GH}(h_x)} = \left\{ h_y \mid \begin{matrix} d(h_x, h_y) < \min(R_F(h_x)); \\ d(h_y, \mathrm{MS}) < d(h_x, \mathrm{MS}) \end{matrix} \right\} - \qquad (1)$$

$\mathrm{SR}_{\mathrm{GH}(h_x)}$ is the product's smallest value, it is denoted as $2R_{\max}$, where minimal stands for decreased integer. The parameters are denoted h_x, h_y, the Relay table function is denoted R_F, and the master station is denoted MS.

Starting condition 1 stipulates that the original state satisfies Equation (1), which assures that the relayed Group Header (GH) falls within the GH band. In addition, by using the least variable, it may be possible to guarantee criterion 2 with a crucial relay GH. GH is selected when this component is used. In addition, it calculates the feasible distance between transmitted GH. If a value is supplied that is incapable of meeting the initial state, the following $\mathrm{SR}_{\mathrm{GH}(h_x)}$ becomes a null collection with GH and delivers data to MS. Consequently, requirement 2 calculates the relaying node closest to MS, followed by the chosen relay node. So, the mix of situations aims for the same level of importance in the administration of GH for MS.

G. Onlooker bee stage

The Onlooker Bee's job is to find something to eat (solution) based on its likelihood value and to implement a local demand on $\mathrm{SR}_{\mathrm{GH}(h_x)}$ [**?**]. When a newly obtained solution achieves a higher fitness rating, it may replace the $\mathrm{SR}_{\mathrm{GH}(h_x)}$. The planned ABC routing system aspires to achieve objective shapes by following the fitness score for accessible single routes. It is characterized as favouring a route to MS by administering the relevant onlooker bee in GH. The conveyed GH is determined to depend on the obtained functionality using Equation (2).

$$P^{B}_{\mathrm{DN}} = \frac{\alpha_{\mathrm{DN}}(p)\delta_{\mathrm{DN}}}{\sum_{x=0}^{\mathrm{SR}_{\mathrm{GH}(h_x)}} \alpha_{\mathrm{DN}}(p)\delta_{\mathrm{DN}}} - \qquad (2)$$

The probability P^{B}_{DN} in which bee b must substitute nodes D and M, respectively. The group in which transmitted GH must be selected using the bee is identified by $\mathrm{SR}_{\mathrm{GH}(h_x)}$. The trial value from node D to node N is denoted as α_{DN}. δ_{DN} specifies the diagnostic data identified in Equation (3).

$$\alpha_{\mathrm{DN}} = \frac{pQ_y}{\sum_{x=0}^{\mathrm{SR}_{\mathrm{GH}(h_x)}} pQ_x} \times \frac{D_y}{\sum_{x=0}^{\mathrm{SR}_{\mathrm{GH}(h_x)}} D_x} - \qquad (3)$$

The weight of routing pQ_y is intended to be the proportion between precipitant power y and the queue size D of the present nodes. D_y reflects the quantity of data between delivery speed x and queue size D. When the MS completes the data payload, an acknowledgement (ACK) is typically sent to the transmitter's GH, which is concerned with delivery likelihood. The upgraded delivery occurs after the ACK signal is received and expressed in Equation (4).

$$D^{*}_{\mathrm{GH}_D} = \frac{D_{\mathrm{GH}_N} + D_{\mathrm{GH}_D}}{2} - \qquad (4)$$

D_{GH_D} refers to the delivery probability for data transmissions and $D^{*}_{\mathrm{GH}_D}$ denotes the improved model of node distribution. The terms heuristic information and trial are α and δ. The onlooker bees transfer the nodes (D_{GH_N}), gather information about the route, and complete MS. C_0 is used to determine the user's GH is used to calculate the target. The discontinuous node collection that selects the node is denoted by $C\{c_0, c_1, \ldots, c_N\}$. The function F calculates the route effectiveness, as shown in Equation (5).

$$F = \frac{G}{\mathrm{rt}_y \times \mathrm{vr}_x} - \qquad (5)$$

G symbolizes the constant, rt_y indicates the route of transmission cost, and vr_x is the variance that reflects balanced power across path borders. Therefore, as the distance between the receiver and broadcaster decreases, the power applied is precisely equal to the square of the transmitted power. It may then be calculated in Equation (6).

$$\mathrm{rt}_y = \sum_{i=0}^{C} R_i = \sum_{i=0}^{C} i \times d^2(Y_{i-1}, Y_i) - \qquad (6)$$

"i" indicates the coefficient of an intermediary node. R_i represents the power consumption along the edges (Y_{i-1}, Y_i). The decreased distance d between broadcaster and receiver (Y_{i-1}, Y_i) is precisely equal to the square of the broadcast length over (Y_{i-1}, Y_i) and to (Y_i), which is computed in Equation (7).

$$R_i = d^2(Y_{i-1}, Y_i) - \qquad (7)$$

The spacing between edge pairs may be adjusted by (Y_{i-1}, Y_i), and the distance is denoted d. The variance is calculated using the specified function using Equation (8).

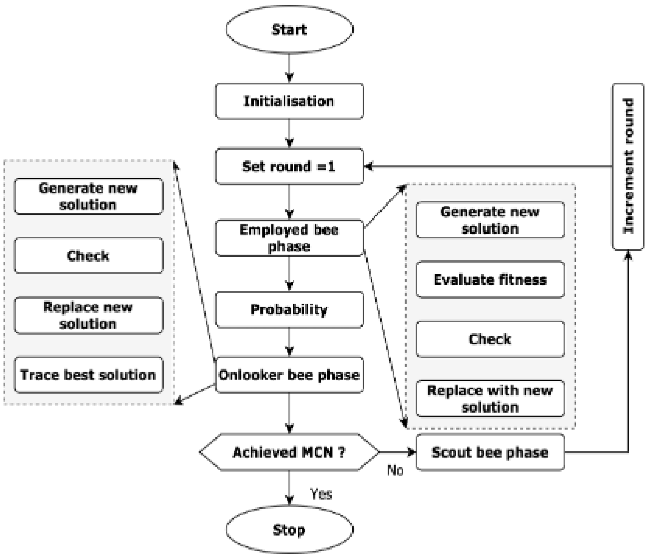

Figure 4. The workflow of the ABC routing optimization method

$$\mathrm{vr}_x = \frac{1}{C}\sum_{i=0}^{C}\left(R_i - \frac{1}{C}\sum_{i=0}^{C}R_i\right)^2 - \qquad (8)$$

In addition, when the F value is applied, the MS obtains the optimal route first. The power consumption is denoted R_i, and the cluster size is denoted C. Therefore, MS transmits data, including route, path acceptability to nodes, and optimum path data. In addition, an employee bee stage and a spectator bee stage have been included for every GH node that locates the optimal relay and executes data broadcasting. It is repeated several times until the MS is reached.

H. Scout bee stage

After calculating the Maximum Cycle Number (MCN), if the best answer is not found, the employed bee abandons the solution and modifies it as a scout bee. Each path (route) has an optimal solution computed for the hop distance between two nodes. Stages such as bees in charge of labour, monitoring, and scouting are used to choose a superior route between two terminals.

In this paper, a unique routing method is proposed. Fig.4 is a simplified depiction of the newly suggested ABC routing concept. Building an efficient routing strategy and establishing inter-cluster networking between all GHs is necessary. When deemed ideal, the freshly created fitness measurement should be compared to the previous fitness measurement, and the conventional fitness measure should be upgraded with the newly produced function for all observing bees. The procedure is finally terminated when the termination requirements are met.

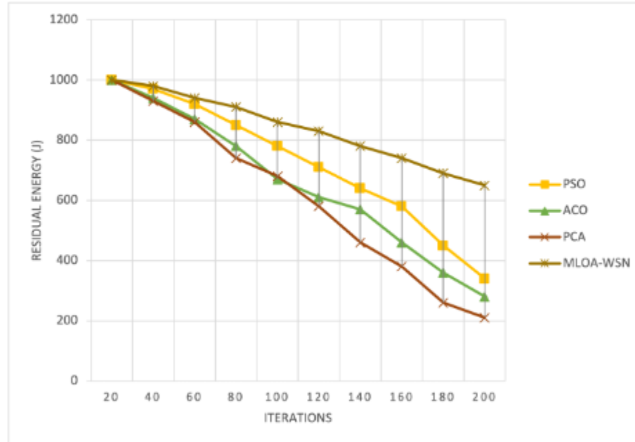

Figure 5. Residual energy analysis of the MLOA-WSN system

4. EXPERIMENTAL ANALYSIS

The suggested MLOA-WSN method's efficiency is evaluated by altering the number of repeated cycles. Several performance metrics, including energy effectiveness, number of living nodes, network lifespan, packet loss rates, and end-to-end latency, validate the MLOA-WSN model's efficiency. A comprehensive comparison study is conducted to guarantee that the MLOA-WSN system operates well. The data are taken from the smart sensor WSN Kaggle Dataset [22].

The WSN dataset contains extensive data collected from a network of sensors spread across several locations. Temperature, humidity, light intensity, and air quality are just a few environmental factors these sensors track in real time. This dataset contains information gathered over a certain time frame that sheds light on patterns and changes in the environment under observation. The accuracy of an algorithm is defined as its capacity to optimally optimize the network parameters to get the targeted performance results. The algorithm's predictions and decisions are compared to the actual network performance data to quantify it. Energy efficiency, latency, and data integrity are all positively impacted by optimization, which in turn is improved by higher accuracy.

The study of the MLOA-WSN system's residual energy and the findings are compared with other available methodologies and are shown in Figure 5. The outputs of the proposed MLOA-WSN system are compared with the results of previously developed models such as the Particle Swarm Optimiser (PSO) [19] [36-40], the Ant Colony Optimiser (ACO) [20], and the Principal Component Analysis (PCA) [21]. The simulation results are analyzed by shifting the number of iterations from 20 to 200 while maintaining a step count of 20. The amount of power that the WSN nodes use grows along with the size of the iteration, which results in a decreased amount of leftover energy in the nodes. The MLOA-WSN system reduces power consumption in the WSN by utilizing multi-objective optimization.

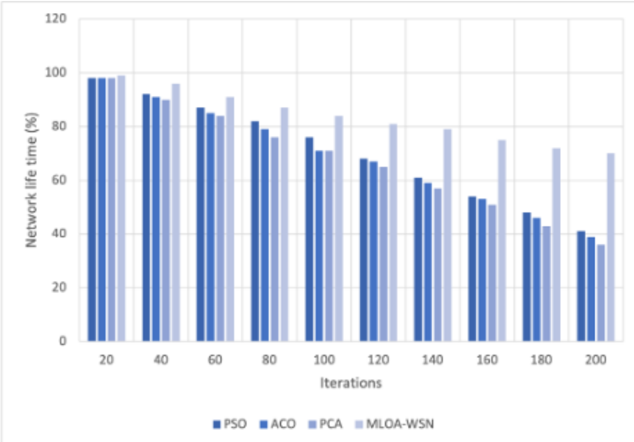

Figure 6. Network lifetime analysis of the MLOA-WSN system

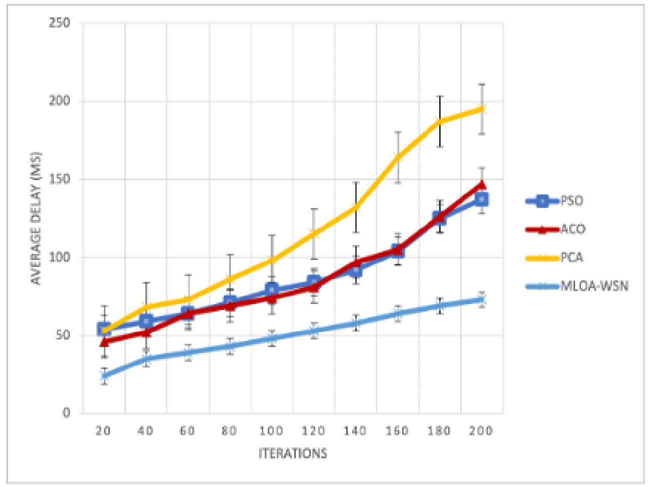

Figure 7. Average delay analysis of the optimizers

The network lifetime analysis of the MLOA-WSN system and the current models are analyzed, and Fig. 6 illustrates the cumulative findings. The amount of time it takes from the beginning of the simulation until half of the WSN nodes are still operational and the other half have perished due to the amount of power they use is what is considered the network life. The MLOA-WSN system that has been presented beats the models already developed by having a longer network lifespan. This is possible because the system uses less power than the other approaches. Multi-objective optimization helps improve the parameters that are still present even more.

TABLE I. Simulation findings of the MLOA-WSN system

Method	Residual energy (J)	Network lifetime (%)	Average delay (ms)	Packet loss rate (%)
PSO	724	70.7	86.9	3.6
ACO	654	68.8	86.1	3.67
PCA	610	67.1	117.1	4.95
MLOA-WSN	838	83.4	50.6	2.43

Analyses are performed on the average delay of the various optimizers, including PSO, ACO, and PCA, as well as the suggested MLOA-WSN system. The results of these analyses are presented in Figure 7. The simulation results are evaluated by shifting the number of iterations from 20 to 200, with each step representing an increment of 20. The corresponding latency in the WSN environment is proportionally more significant whenever the iteration size increases. The increasing number of cycles results in the processing of WSN data more times, which causes latency to rise. However, this leads to better optimization and simulation efficiency levels, with fewer errors occurring throughout the computing stage.

Analyses are performed on the packet loss rate analysis of the proposed MLOA-WSN system, and the findings are compared with those of existing models. Figure 8 presents the findings of a comparison between the MLOA-WSN system and the models that are already used. One way to determine experimental packet loss is to add all the missing packets throughout the simulation. Another way to do it is to divide that total by the overall amount of communicated packets. This ratio is then used to get the empirical packet loss rate. As a result of the enhancements made to the transmission process by the proposed MLOA-WSN system with multi-objective optimization, the rate at which packets are lost in the environment has decreased. By maximizing energy efficiency, decreasing latency, and enhancing data integrity, the MLOA-WSN algorithm greatly improves network performance.

It accomplishes a high packet delivery ratio and mitigates interference to decrease packet loss effectively. The wider ramifications of these enhancements for creativity, cost reduction, and scalability in wearable WSNs and IoT contexts are substantial. With its capacity to tackle important problems and enhance network stability, the algorithm has great promise for broad use in many industries, leading to better and more efficient IoT solutions.

The simulation results after considering the typical amount of remaining energy, lifetime, average latency, and package loss rate are calculated for both the already-in-use systems and the planned MLOA-WSN system. The findings of the comparisons are shown in Table 1, which includes the graphs. The findings assure that the MLOA-WSN system will have the maximum performance across all criteria. These outcomes were achieved by multi-objective optimization, which improved system performance across all relevant metrics when applied in WSN settings. Wear-

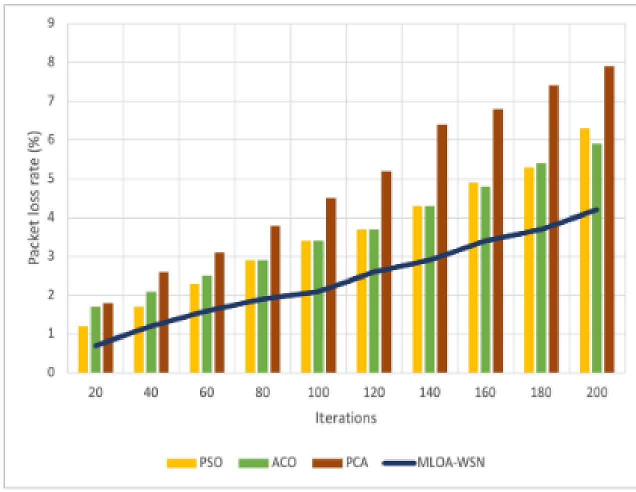

Figure 8. Packet loss rate analysis of the proposed MLOA-WSN system

able sensors are revolutionizing healthcare by continuously tracking vital indications, including heart rate, blood pressure, and glucose levels. Athletes monitor their speed, acceleration, and muscular activity using wearable sensors. Wearable sensors are becoming more common for forces to track their movements, health, and environmental factors in military applications. A great deal of private and sensitive information, including health indicators, location data, and activity levels, is gathered by various wearable sensors. When developing algorithms, it's important to maintain users' rights to data management, especially the capacity to give or withdraw permission, in mind. Data should be anonymized whenever feasible. Optimization algorithms should use efficient encryption methods to protect data while it is being sent and stored. To further protect against ever-changing vulnerabilities and threats, it is essential to conduct security audits and upgrades frequently. Utilizing secure data processing procedures is one way to protect user data from hackers.

5. CONCLUSION AND FUTURE SCOPE

Data gathering considerably mitigates the current problems of redundant and apparent redundant sensory data in this research. It is conducted to extract valuable data, thereby minimizing transmission costs. This study proposes a unique technique for data aggregation using the Machine Learning-based optimization algorithm for WSN (MLOA-WSN), which is based on power, distance, latency, and density. This study proposes a unique technique for data aggregation using the Machine Learning-based optimization algorithm for WSN (MLOA-WSN), which is based on power, distance, latency, and density. The testing outcomes vary depending on the number of nodes. Regarding adaptability of networking, data distribution, packet loss, performance, and network effectiveness, the suggested MLOA-WSN algorithm has obtained improved assessment measures that have superior outcomes compared to the current approaches. The proposed approach reduces the overall distance traversed by a mobile sink to collect information from every device in the network's periphery, therefore improving the network's performance. The method was evaluated under various settings, and the outcomes indicated that the suggested algorithm outperformed previous techniques in terms of decreased delay and solution precision. Obtaining an ideal solution with great precision may require more investigation into the influence of different factors. The existing process for findings of the MLOA-WSN system is a value of 2.43, packet loss rate analysis of 7.6 and Average delay analysis of the optimizers for 224. Due to its pervasiveness, WSN is one of today's most pressing demands. Finally, the suggested optimization technique that relies on machine learning might greatly affect the creation and implementation of reliable wearable WSNs in Internet of Things environments. This study opens the path for more reliable and efficient Internet of Things (IoT) solutions by tackling important problems, including interference, data integrity, scalability, and energy consumption. As a result, innovation can grow, and people's lives can be improved in many areas. However, implementing advanced machine learning algorithms can be computationally intensive. Future studies will use WSN for undersea acoustical detection structures, intelligent detection and frequency leadership, and safety and data administration. For sensor technology, IoT implies that sensors can connect with various devices and systems, resulting in a fully integrated ecosystem that can adapt to changing circumstances and automate activities.

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