



Clustering Based Hybrid Optimized Model for Effective Data Transmission

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Abstract. The Internet of Things (IoT) is a system of unified gadgets that can conversation data and operate in tandem thanks to the web. When it comes to the longevity of a network, smooth data production is crucial, and wireless sensor networks (WSN) play a key character in the IoT in this regard. Despite the IoT's usefulness in many areas, it still faces obstacles in the form of security, energy, load balancing, and storage. Clustering and multi-hop routing are two methods used in the architecture of an IoT-assisted WSN to reduce energy consumption. This research therefore provides a novel effective hybrid optimization strategy for choosing cluster heads. In to adjust the white shark optimizer's (WSO) stochastic behaviour while it seeks out food, the suggested method makes use of the whale optimization approach (WOA). The new HWSO was also tested against a group of contemporary meta-heuristic methods, such as the artificial optimizer (GTO), the coyote optimization algorithm (COA), and the original WSO. Finally, the proposed network is put through its paces by making use of NS-3.26's extensive simulation features. Improvements in packet delivery ratio (PDR), latency, energy consumption, number of dead nodes, and longevity of the network may be shown in the simulation results.

Keywords: Wireless networks · White shark optimizer · Internet of Things · Clustering · Whale optimization approach · Coyote optimization algorithm · Data Transmission

1 Introduction

These days, IoT and mobile edge computing (MEC) are commonplace tools for anticipating and meeting future technical requirements. Innovations in technology have mostly targeted information transmission needs, lightening the burden on the network, and increasing throughput [1]. Reliable platforms, smart cities, and transportation all rely on networks that can handle minimal delays, store large amounts of data, and operate in mission-critical areas of operation [2]. Scientists are paying more attention to the development of autonomous networks for Internet of Things devices as their prevalence grows [3]. The primary objective of the network executive idea is to design a multi-hop network that makes efficient use of electricity by linking nodes at the source and the destination using mobile phone relay nodes (RNs) [4]. Increased interest in (WSNs) can

be attributed to the quick expansion of MEMS technologies and wireless networks in recent years [5]. The IoT would not be complete without WSN. As a result, WSN applications have connected with the human, digital, and material spheres. Typically, WSNs are made up of a large sum of minor sensors spread out crossways a big region, and base stations (BS) that collect data from these sensor nodes.. Clustering is the process of dividing a network into smaller, more manageable pieces [7]. CH is the initial node in the routing process, and it is responsible for delivering the message to its eventual destination [8].

Clustering consumes some of the network's radio resources [9]. During network clustering, nodes can do computations to arrange its nearby nodes clusters. The cluster structure's robustness relies heavily on the care taken during cluster formation and CH selection [10]. Rearranging cluster nodes (CMs) is one way to make structural changes to an existing cluster. The cluster maintenance signaling also makes use of the network's radio resources. Costs associated with forming and keeping a cluster are measured in terms of the time spent translating control messages. The effectiveness of a clustering model is measured in terms of numerous factors, such as the size of the cluster and how long it takes to construct [11]. Using AI techniques, we can classify networks into different groups [12]. The primary problem with these approaches is that they are computationally intensive and so cannot guarantee optimal results. They move too slowly toward optimal results.

Energy consumption and transmission power are inseparable. If we select either a high or low transmission power, SNs will expend more energy. To reduce energy waste, the transmission power should be kept between its extremes. The concept of biological evolution forms the basis for evolutionary algorithms (EA) [13]. Evolutionary approaches, learning classifier systems, and genetic algorithms are all part of EA. Evolutionary algorithms are a good option to try if previous methods have failed. In the face of seemingly intractable [14] problems, evolutionary techniques are often embraced. A near optimum solution to an unresolved situation is acceptable even if EA is computationally expensive. An atmosphere conducive to the natural selection of effective solutions to the issue at hand will be established [15]. Using these biological algorithms, the optimal solution to problems associated with constructed habitats may be found. The scalability issue is addressed by grouping nodes together and allowing them to share their geographical coordinates.

The following are some clarifications that help highlight the limitations of the described methods:

Premature and sluggish convergence rates are a problem for several of the described meta-heuristic optimization techniques, leading to entrapment in local optima.

In addition to needing a lot of data to train the neural network-based method, several other published systems have the drawback of taking a long period and requiring a lot of work to implement.

To overcome these restrictions, this study introduces a hybrid strategy that combines the white (WSO) with the (WOA) in order to alter the behaviours of the unique WSO while it forages for food. These are some of the ways in which this work contributes:

- To improve the misuse phase of the standard (WSO), we present a hybrid version of the algorithm that uses the whale optimization algorithm's spiral updating position strategy.
- The suggested HWSO is tested against the generic white shark optimizer (GTO), the clustered optimal algorithm (COA), and the white shark optimizer itself for accuracy.

2 Related Works

Work objects were presented by Arunachalam et al. [16] to provide a unique energy-efficient process by combining the features of sophisticated aggregation approaches. To pick the CH optimally according to energy, distance, and weight value, a spider monkey optimization (SMO) based protocol is designed. The suggested technique has been evaluated using a number of performance indicators, and the findings have been compared to those of other, more current state-of-the-art models to demonstrate its superiority.

Using a (E-RARP) and a clustering method (GEC), Gunigari and Chitra [17] have created a hybrid Energy Efficient and Reliable (ACO). E-RARP is a novel ACO-based routing protocol for WSNs that is both energy efficient and reliable. The proposed protocol ensures consistent connectivity and high-quality lines of communication to boost power.

In order to balance network security and energy efficiency, Nagaraj et al. [18] propose the secure encryption (SERPPA). When it comes to backing up and keeping tabs on the network's nodes, SERPPA has a central entity known as a cluster head.

Nirmaladevi and Prabha [19] have been concentrating on developing a routing system that can function even when selfish nodes are present. The hierarchical clustering method is used by (SN-TOCRP). The Fuzzy-based Crowd Search Algorithm is inspired by nature and is used to choose cluster Heads (CH). To identify nodes that are acting in their own self-interest, we introduce an authentication approach that verifies the authority of the cluster leaders.

Oppositional Cuckoo Search Optimisation based Clustering with Classification Model for Big Data Analytics in Healthcare Environment has been proposed by Gayathri [20], who also creates a Map Reduce (MR)-based, enhanced metaheuristic algorithm-based clustering and classification model.

3 Proposed System

3.1 Environment-Adaptive Hierarchical Clustering

In this scenario, it is assumed that M nodes have been appropriately placed in the placement region and that their coordinates are known in advance. These M nodes would be considered the first clusters in the aggregate hierarchical clustering algorithm's theoretical framework:

$$C_i = \{X_i\}, i \in M \quad (1)$$

where C_i denotes the cluster's i^{th} iteration. Each round of clustering would use the biggest Euclidean distance between any two groups as the clustering cost. The two nearest clusters would then merge into a novel cluster until the termination illness is met or the requisite sum of clusters is attained.

Assume that $C(M + a)$ includes X_i, X_j after many clustering processes, furthest distant from one another among the nodes they enclose. Using the HC procedure's idea of the biggest distance among clusters, we may express the largest reserve among these two clusters as $D(C_{(M+a)}, C_{(M+b)})$.

$$D(C_{M+a}, C_{M+b}) = D(X_i, X_k) \quad (2)$$

where $M + a$ and $M + b$ characterize the label of the clusters.

In this paper, the chief distance among the organized nodes D_{max} is designated and attuned to serve as the clustering finish threshold T .

$$= \sigma \max \left\{ \frac{T = \sigma D_{max}}{\sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2}} \right\}, i, j \in M, i \neq j \quad (3)$$

where $X_i = (X_i, Y_i), X_j = (X_j, Y_j)$ signifies the nodes, and σ signifies the applied factor, which is defined as the ratio within the confidence distance.

3.2 HCEH-UC Routing Procedure

This work proposes a distributed data transmission mode modification approach for WSN nodes to use in order to achieve optimal data transmission. The fatigued node might be recharged in time to make for the next cycle, and the cluster head may be switched between nodes based on the amount of energy left. To ensure the proper functioning of WSNs with high-energy efficiency, each cluster may adaptively complete the data collecting cycle. Therefore, the proposed HCEH-UC routing algorithm allows for continuous coverage of the desired region by EH-WSNs. Table 1 displays the radio energy consumption model used to determine the WSNs' data transmission energy requirements.

Table 1. The energy ingesting in radio broadcast and reception manner.

Mode	Energy-Consumption
transmission/reception manner	$50(\text{nJ} \cdot \text{bit}^{-1})$
free-space evidence amplification (ε_{fs})	$10(\text{pJ} \cdot \text{bit}^{-1} \cdot \text{m}^{-2})$
multipath-fading info amplification (ε_{mp})	$0.0013(\text{pJ} \cdot \text{bit}^{-1} \cdot \text{m}^{-4})$

A wireless propagation model is recognized using the multipath attenuation models, and the energy required to communicate k bits of data is given by the formula E_{Tx} :

$$E_{Tx}(k, d) = E_{Tx-elec}(k) + E_{Tx-amp}(k, d) = \{E_{elec} * k + \varepsilon_{fs} * k * d^2,$$

$$d < d_0 E_{elec} * k + \varepsilon_{mp} * k * d^4, d \geq d_0 \quad (4)$$

where d is the distance to be sent, d_0 is the distance is the broadcast energy, and ET_{xamp} is the intensification energy needed to transmit data to distance d :

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}} \quad (5)$$

At the same period, the energy obligatory to receive k – bit data can be portrayed as (6):

$$E_{Rx}(k) = E_{Rx-elec}(k) = E_{elec} * k \quad (6)$$

The data is then compressed by the CHs before being sent to the base station or the end user end. The total amount of data that a cluster of Q nodes needs to send to the base station in one cycle is k_{Bs} bit, the base station is dBs , the amount of data that the q th node in the cluster needs to send to the cluster cycle is k_{qs} bit, and the distance among q and s is d_{qs} .

The energy used by the cluster head node s during a single cycle of the network can be broken down into the following parts (E_{Rx} = energy used to receive data from other nodes, E_{Df} = energy used for data fusion, and E_{Tx} = energy used to transmit data package to base post B):

$$E_{Bs} = E_{Rx}(k_{Bs}) + E_{Df}(k_{Bs}) + E_{Tx}(k_{Bs}, d_{Bs}) = E_{elec} * k_{Bs} + E_{DA} * k_{Bs} + E_{Tx-elec}(k_{Bs}) + E_{Tx-amp}(k_{Bs}, d) \quad (7)$$

where E_{DA} signifies the energy ingesting continuous for data fusion.

Assume the node q conveys k_{qs} bit data to the cluster s in one data broadcast cycle:

$$\sum_{q=1}^Q k_{qs} = k_{Bs}. \quad (8)$$

Thus, the energy ingesting E_{qs} of the q th node to transmission these data can be labelled as (9):

$$E_{qs} = E_{Tx-elec}(k_{qs}) + E_{Tx-amp}(k_{qs}, d), q \neq s. \quad (9)$$

The cluster head node should go to sleep mode to conserve energy when its battery life is too low to sustain routing operations. The data transmission job is so taxing that the sleep node can hardly carry it out. Therefore, the novel cluster head node would be chosen based on the location data and status of the other nodes in the cluster in an effort to achieve UC-EH, or continuous target coverage. Let's pretend that the Estimation is the power needed to transmit data between nodes.:

$$E_{estimation}(s) = E_{Bs} + \sum_{q=1}^Q E_{qs}, q \neq s \quad (10)$$

where the $E_{estimation}(s)$ includes the energy obligatory E_{qs} for nodes energy can be characterized by E_{rest} , and the r is adopted to signify the likelihood of being designated as a cluster head for the q^{th} .

$$\rho(q) = \left\{ 1 - \frac{E_{estimation}(q)}{E_{rest}(q)}, q \in G0, \quad q \notin G \right. \quad (11)$$

where G is the group of nodes that haven't been chosen to send data during the current round of transmission. As the distance between nodes and the grew, so did $E_{estimation}$. Since the successor CH's data delivery energy needs to be low and the successor CH's leftover energy needs to be high, the node with the highest probability r develops the successor CH.

The suggested clustering technique would produce node clusters that are uniformly dispersed over the target detection region, with nodes in each cluster being closer together than they are to the base station. As a result, the energy needs of the cluster's leader node are significantly higher than nodes. The energy amassed by the cluster head must sustain communication with the base station, communication with the cluster nodes, and interaction with the cluster's successor cluster head.

3.3 Proposed Clustering Algorithm: Hybrid Model

3.3.1 White Shark Optimizer (WSO)

Braik et al. [23] presented the (WSO), one of the newest meta-heuristic methods. The authors were inspired to create this algorithm by the complex behaviors of great white sharks, which include the use of highly developed senses of hearing and smell. White sharks are gorgeous and well adapted hunters; they use their powerful jaws and fins to capture prey such as dolphins, small whales, crabs, seabirds, and seals. Great white sharks employ a technique of surprise and rapid movement to ambush their victim, after which they strike with devastating force.

There are three different actions that must be taken in order to devour the prey (food source): moving towards the prey utilizing the hesitations generated by the prey's movement in the waves, randomly searching for depths, and identifying nearby prey. The great white sharks can then use these processes to adjust their postures and find the optimal solutions. The WSO may be modeled by creating an initial population of solutions in a matrix. Where N is the population size and d is the issue dimension, the size of the initial population matrix is N :

$$w = \left[w_1^1 w_2^1 \cdots w_d^1 w_1^2 w_2^2 \cdots w_d^2 : w_1^n : w_2^n : \cdots : w_d^n \right] \quad (12)$$

where w_j^i characterizes the i th white shark site in the j th measurement. It can be intended based on the lower (lb_j) and upper (ub_j) limits of the search as:

$$w_j^i = lb_j + rand \times (ub_j - lb_j) \quad (13)$$

where $rand$ is an integer chosen at random between zero and one. Using Eq. (12), an initial solution's fitness is computed, and an updating procedure is set into motion if the

new location is superior to the old one. The great white shark detects the position of its food by the hesitance of its waves and then swims in undulating motions at a pace:

$$v_{k+1}^i = \mu \left(v_k^i + \rho_1 [w_{gbest_k} - w_k^i] \times c_1 + \rho_2 [w_{best}^{v_k^i} - w_k^i] \times c_2 \right) \tag{14}$$

where v_{k+1}^i and v_k^i are w_{ki} is the site of the i th white shark in repetition k ; c_1 and c_2 are random statistics in the range $[0, 1]$; $w_{best}(v_{ki})$ site to the swarm during iteration k ; and v_{ki} is the index vector sum i for sharks obtaining the best location, and it can be:

$$v = [n \times rand(1, n)] + 1 \tag{15}$$

The parameters ρ_1 and ρ_2 that control the w_{gbest_k} and $w_{best}^{v_k^i}$ best effects on w_k^i ; they can be subtracted as shadows:

$$\rho_1 = \rho_{max} + (\rho_{max} - \rho_{min}) \times e^{-\left(\frac{4k}{K}\right)^2} \tag{16}$$

$$\rho_2 = \rho_{min} + (\rho_{max} - \rho_{min}) \times e^{-\left(\frac{4k}{K}\right)^2} \tag{17}$$

where ρ_{min} and ρ_{max} are K is the maximum number of iterations, $\rho_{min} = 0.5$, $\rho_{max} = 1.5$, and = the initial and inferior velocities to improve the great white sharks' movements. The convergence rate of the WSO may be analyzed with the use of the correction factor, denoted by the term in Eq. (14):

$$\mu = \frac{2}{|2 - t - \sqrt{t^2 - 4t}|} \tag{18}$$

where t is the acceleration factor of the procedure.

Great white sharks, as was previously said, devote the vast majority of their time to hunting for high-value prey. As a result, their locations shift as they approach their prey, which they do by listening to the waves caused by the prey's movements or by detecting the prey's scent. Great white sharks in this scenario wander to seemingly random locations while they hunt for food; this behavior may be modeled as follows [21]:

$$w_{k+1}^i = \{w_k^i \times \neg \oplus w_0 + ub \times a + lb \times b \text{ if } rand < mvw_k^i \\ + \frac{v_k^i}{f} \text{ if } rand \geq mv \tag{19}$$

where \neg is the negation operator, Eqs. (20) and (21) define binary vectors a and b , Eq. (22) computes a logical vector w_0 , and Eq. (23) determines the frequency of the great white shark's wavy movements.

$$a = sgn(w_k^i - ub) > 0 \tag{20}$$

$$b = \text{sgn}(w_k^i - lb) < 0 \tag{21}$$

$$w_0 = \oplus(a, b) \tag{22}$$

$$f = f_{min} + \frac{f_{max} - f_{min}}{f_{max} + f_{min}} \tag{23}$$

where f_{max} and f_{min} are the highest and lowest frequencies at which the great white shark’s movements undulate. The great white shark’s propulsion power, denoted by the parameter mv , is raised iteratively as shown in [23]:

$$mv = \frac{1}{a_0 + e^{\left(\frac{0.5K-5}{a_1}\right)}} \tag{24}$$

where a_0 and a_1 are two parameters for controlling exploration and exploitation. The use of mv speeds up the search process and fortifies the WSO’s exploratory and exploitative tendencies. Because of this benefit, the author decided to use this sort of method to address the addressed issue. Here’s how you may model how a great white shark might move to get closer to its prey:

$$w_{k+1}^i = w_{gbest_k} + r_1 \vec{D}_w \times \text{sgn}(r_2 - 0.5) \quad \text{if } r_3 < S_s, \tag{25}$$

where w_{k+1}^i characterizes the i th countless white shark new site with regard to its prey:

$$\vec{D}_w = \left| \text{rand} \times (w_{gbest_k} - w_k^i) \right| \tag{26}$$

The parameter S_s in Eq. (27) is active to label the olfactory senses when subsequent it prey thoroughly; it can be intended as follows [23]:

$$S_s = \left| 1 - e^{-\frac{a_2 k}{K}} \right| \tag{27}$$

where a_2 is a parameter used to control the examination/misuse behaviors.

3.3.2 The Proposed Hybrid WSO-Based Methodology

In the simplest procedure of the WSO, the sharks move toward their prey spot using a single approach, which may cause the algorithm to miss additional favorable nodes in the vicinity. Therefore, in this study, the WSO has been combined with a different method based on a spiral shaped path in order to improve the exploitation behavior of the original WSO. According to the whale optimization algorithm (WOA), the application of the spiral-shaped route was motivated by whale prey spots. The following correlation represents the great white shark’s spiraling journey to its meal:

$$W_{t+1}^i = \vec{D} \cdot e^{hl} \cdot \cos(\cos(2\pi l)) + W_t^* \tag{28}$$

$$\vec{D} = \left| \vec{W}^* - \vec{W} \right| \quad (29)$$

where \vec{D} is the great white shark's prey's distance from the shark, the constant h used to define the logarithmic spiral's form, and a random value l in the interval $[1]$. The great white shark's approach to its prey, as in Eq. (25), may be altered using the spiral equation in the following way:

$$w_{t+1}^i = \{w_{gbest_k} + r_1 \vec{D}_w \times \text{sgn}(r_2 - 0.5) \text{ if } r_3 < S_s \vec{D} \cdot e^{bl} \cdot \cos \cos(2\pi l) + w_t^* \text{ if } r_3 < S_s \quad (30)$$

The primary framework of the proposed HWSO is summarized in pseudo code (see Algorithm 1) below when applied to the parameter estimation and optimization issue of the battery model. The first random set of solutions is generated by assigning bounds to the model parameters. Then, the relevant values for the goal function's starting point are determined using Eq. (11).

4 Results and Discussion

We evaluate the effectiveness of our suggested protocols by simulating them with varying numbers of nodes, varying simulation times, varying the fraction of faulty/failure nodes, and varying the speed at which the nodes may move. Our simulation lasted for 100 s, during which time 100 mobile nodes were spread out throughout a 500 m by 500 m region of the network as shown in Table 1. We analyze nodes with a given 100 energy to start, and CBR traffic is assumed as the source type (Table 2).

Table 2. Default simulation parameters.

Parameter	Value
Topology dimension	500 m × 500 m
Mobility perfect	Random way point perfect
Propagation Model	Free space propagation perfect
Sum of Nodes	100
Simulation Period	100 s
Early Energy	100 J
Mobility Speed	10 m/s
Sum of Fault nodes	0
Pocket loss rate	0
Antenna perfect	Omni directional
MAC type	802.11
Traffic Kind	CBR

4.1 Performance Metrics

In the simulation studies, we employ the following performance measures [22, 23].

4.1.1 Packet Delivery Ratio (PDR)

The packet delivery rate is the fraction of total data packets transmitted that arrived at their target node. PDR demonstrates a protocol's efficiency in delivering data over a network. Here is how the PDR is calculated:

$$PDR = \frac{\sum P_d}{\sum P_s} \times 100 \quad (31)$$

In this equation, P_d characterizes the sum of packets delivered and P_s characterizes the sum of packets sent.

4.1.2 Throughput

How many megabits per second (Mbps) of data have been sent and received across the network in a certain time period. It measures both quality and efficiency. A low percentage of lost data packets during transmission indicates a high throughput. Here is how we quantify it:

$$G = \frac{\sum B_r \times 8}{T} \times 10^6 (Mbps) \quad (32)$$

In this equation, G is the throughput, B_r is the entire sum of bytes conventional, and T is the simulation time.

4.1.3 End-to-End Delay (E2E)

The time it takes for a packet of data to arrive at its final destination after being sent from the sending node. It's sometimes referred to as "One-Way Delivery" (OWD). Delays of any kind fall under this category. The sending node checks its routing database to see if there is a path to the destination before sending any data packets. The source node initiates route discovery by broadcasting RREQ signals to its nearby nodes if no route is known to exist. This will keep happening until one of the nodes sends back the sender in accordance with the AOMDV protocol. Based on the fitness function in Eq. (11), the source node will determine the optimal route and only use this destination node. The whole end-to-end (E2E) lag time is computed as:

$$E2E = \frac{\sum_{i=0}^n R_i - S_i}{n} \quad (33)$$

Here, n is the total sum of packets positively received, R_i is the time at which the i th packet arrived at its destination node, and S_i is the time at which the i th packet was transmitted from its source node [23]. The timestamps S_i and R_i are gathered from the application layers.

4.1.4 Energy Consumption

During the simulation period, this is the cumulative total of the energy used by the network’s nodes. The formula is as follows:

$$E = \sum_{i=0}^m I_i - E_i \tag{34}$$

The energy consumption, denoted by E, the initial energy, denoted by I_i, and the final energy, denoted by E_i, of node i at the conclusion of the simulation period for all m nodes are all denoted by these symbols.

4.2 Validation Analysis of Proposed Model

In this research work, the existing models are implemented and their results are averaged for every parameter that is shown in Table 3, 4, 5 and 6.

Table 3. Throughput analysis of different models

Simulation Period (Seconds)	20	40	60	80	100
GTO	69	65	61	59	58
COA	70	68	65	63	60
WSO	72	71	69	68	67
HWSO	83	80	77	74	71

In above Table 3 represent that the Throughput analysis of different nodes and different models. In this analysis the proposed model reaches the 20th node throughput as 83 and the 40th node as 80 and 60th node throughput as 77 and also the 80th node throughput as 74 and finally the 100th node throughput as 71 repressively.

Table 4. Energy consumption with sum of nodes by different models

Number of nodes	20	40	60	80	100
GTO	35	40	45	50	60
COA	32	38	40	48	58
WSO	30	36	38	46	55
HWSO	22	26	30	38	42

In above Table 4 represent that the Energy consumption with sum of nodes analysis we used different nodes and different models. The proposed model in range of 20th node the value reached 22 and 40th node value as 26 and the 60th node value as 30 and the 80th node value as 38 and finally the 100th node the energy consumption value as 42 respectively. In Fig. 3 our proposed model takes less delay if the no of nodes increased.

Table 5. End-to-end delay with sum of nodes.

Sum of nodes	20	40	60	80	100
GTO	40	43	48	50	55
COA	35	38	43	48	50
WSO	30	35	38	43	53
Proposed	25	29	34	38	42

Table 6. PDR with sum of nodes.

Sum of nodes	20	40	60	80	100
GTO	76	55	50	45	40
COA	75	50	48	43	44
WSO	74	53	46	40	38
Proposed	83	65	60	58	55

In above Table 5 represents End-to-end delay with sum of nodes and Table 6 represent that the PDR with number of nodes. In this analysis we used different nodes and different models. The proposed model in range of 20th node the value reached 83 and 40th node value as 60 and the 60th node value as 60 and the 80th node value as 58 and finally the 100th node the PDR value as 55 respectively.

5 Conclusion

The determination of this research was to develop a novel hybrid optimization approach for improving WSNs' energy efficiency and durability. The Internet of Things (IoT) network's main level consists of randomly distributed nodes that exchange data using various gathering mechanisms. The described method then largely uses a hybrid model to choose CHs and arrange clusters. To do this, we proposed a novel hybrid meta-heuristic strategy based on a WSO and the WOA. The WOA improved the WSO's stochastic behavior in its hunt for food. The suggested method's significance lay in the fact that it solved many of the issues seen in earlier approaches, the most significant of which was becoming stuck in local optima. Once the best paths have been determined, the CHs will use them to send data to the BS. Instead of using a standard search approach, the suggested protocol employs an energy-saving strategy in which the best CHs are selected using an enhanced efficient function. These steps improve the efficiency of the procedure. We compared the effectiveness of the proposed protocol to that of other well-known cluster-based conventions to show that it holds up across a variety of presentation criteria. The artificial (GTO), the coyote optimization algorithm (COA), and the rudimentary WSO were all used to compare and contrast the method to other optimizers. Future improvements to the suggested method's energy efficiency might come from data aggregation and sleep scheduling systems.

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