Optimizing Hybrid Metaheuristic Algorithm with Cluster Head to Improve Performance Metrics on the IoT

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Research Article

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Optimizing Hybrid Metaheuristic algorithm with Cluster Head to improve performance metrics on the IoT

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Abstract

The Internet of Things (IoT) has subsequently been applied to a variety of sectors, including smart grids, farming, weather prediction, power generation, wastewater treatment, and so on. So if the Internet of Things has enormous promise in a wide range of applications, there still are certain areas where it may be improved. Designers had focused our present research on reducing the energy consumption of devices in IoT networks, which will result in a longer network lifetime. The far more suitable Cluster Head (CH) throughout the IoT system is determined in this study to optimize energy consumption. Whale Optimization Algorithm (WOA) with Evolutionary Algorithm (EA) is indeed a mixed meta-heuristic algorithm used during the suggested study. Various quantifiable metrics, including the variety of adult nodes, workload, temperatures, remaining energy, and a target value, were utilized IoT network groups. The suggested method then is contrasted to several cutting-edge optimization techniques, including the Artificial Bee Colony method, Neural Network, Adapted Gravity Simulated annealing. The findings show that the suggested hybrid method outperforms conventional methods.

Keywords: Cluster head, IoT, Meta-heuristic Method, Whale optimization algorithm, wireless network

1. Introduction

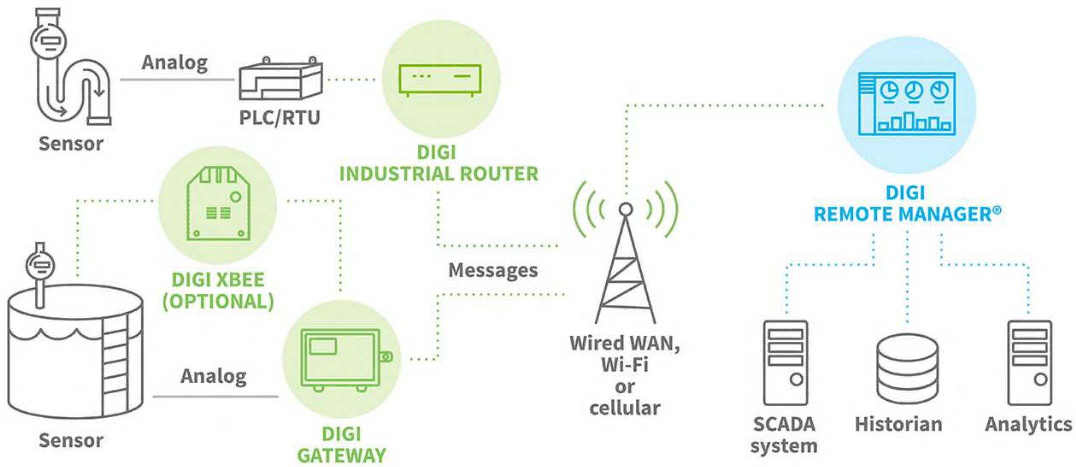
The IoT is indeed a platform that connects everything that can send data, including wireless communication, robotics, wearables, and automobiles. Each IoT device has its identification. The IoT has exploded in popularity during the last year. IoT is used in the construction of smart communities, residential surveillance cameras, agricultural, and healthcare systems, among other things [1]. Even though IoT is utilized in a wide range of applications, the effectiveness of such implementations is contingent on the resolution of several issues. Incorporation from several allowing technologies which cope with storing, able to sense, computing power, and interconnection; accessibility; dependability; showings; and Quality of Service (QoS) are among the difficulties of effective IoT execution [2-3].

The focus of this article is to tackle the power management problem statement for wireless sensor nodes throughout the IoT. IoT devices require a lot of electricity since their wireless sensors constantly perceive and create a lot of data. As a result, the lifetime of sensor devices may be reduced, as well as the network's long-term viability. We need to optimize the electricity usage of WSN sensors to overcome this problem [4] There will be numerous sensor network nodes inside the IoT device. All of these nodes attempt to connect with the IoT Base Station (BS), potentially overwhelming the BS and causing duplicate data to be transmitted [5]. To counter this disadvantage, a collection of terminals is split into many groups, each with its CH. All the other cluster members transmit messages to the CH. The data will then be consolidated by each CH and sent to the IoT BS. CHs are chosen in each cluster based on a variety of performance criteria such as heat, load, range, power consumption from either the CH to the IoT BS and latency. The IoT-based WSN design is depicted in Figure 1.

The new cluster sizes, such as rising groups and reduced groups, constitute a critical problem in this architecture, reducing performance characteristics considerably since the range between the BS and CHs fluctuates too much for certain networks. It has a long processing time, which causes delays and loads. Due to their excessive power consumption, the previous methods fail [6,7]. Several meta-heuristic and adaptive optimization models were used to conserve power with this goal in mind. To save energy, all of these programs concentrated on the ongoing nodes and let the others sleep. IoT, on the other hand, takes more energy owing to a variety of concerning data flow, strain, and heat.

As a result, there's no need to provide a power Authentication scheme that normalizes power and therefore achieves net durability and balance. To do this, a combination of Whale Optimisation Computation Annealing is utilized in this research to choose the best CH in an IoT network [8]. By exploring the most significant areas indicated by the WOA method, this mixed-method uses

EA to improve utilization. The following is how the remainder is organized: Recent research on energy optimization of WSN devices in the IoT system is discussed in Section 2. Section 3 reviews the basics of the proposed system. Section 4 elaborates on the proposed framework. The results of the experiments are analyzed in Section 5. Results and other efforts are detailed in Section 6.



2. Materials and Methods

Many efforts have been made to extend the life of IoT networks. In this area, we've taken a look at some of the most well-known works. The authors of [9] proposed employing a metaheuristic method called quantum particle swarm to enhance the lifetime of the IoT systems to use a cooperative Multiple-Input-Multiple-Output strategy (MIMO). For every trip, QPSO seeks to automatically select the optimum collaborative numerous transmitter and receiver modules, leading to increased life. The researchers used additive white noise for similarity communications throughout this study.

The researchers employed three-hop networking in their experiments, and a simulation was run to test the channel's battery capacity for only 2 * 2 MIMO and 3 * 3 MIMO. The writers of Standard 10 suggest a neuro-fuzzy rules grouping method for improving edge efficiency. The method is designed to find the optimal CH and means knowledge effectively, lengthening the life of the network [10]. The calculation of CH energy consumption and CH to drain node range provides an overview of system performance. The simulation results show that the use of neuroblur technology reduces power consumption while increasing the life of the grid. The researchers of this paper concluded that all nodes in the network are trustworthy.

The researchers of [11] provide a methodology for determining the optimal cluster prefix. Because IoT devices have a shorter battery life, they have far less capacity and a shorter available bandwidth. The information obtained by the researchers was sent to IoT BS using this suggested data transmission. To enhance the network's durability, two of the finest clusters headers are picked in the same clusters during the CH selection procedure. The method of selecting dual CHs is an information entropy info fusion. The sensitivity information would then be utilized for categorization and fusing, data transfer, and categorization outcome blending [12].

The researchers of [13] use Self-Adaptive WOA (SAWOA) to create a power Channel access strategy for the WSN-IoT network. Latency, duration, energy, strain, and heat were all taken into account while determining the optimal CH efficiency. The suggested model is compared against several algorithms based on WOA, including ABC, CH selection methods, etc. The simulation model's findings extend the network's lifetime.

The authors of [14] utilize a unique MOFGSA method in choosing the optimal CH. The power of each node generates many messages for efficient transit through the IoT. The FGSA approach combines fractional and GSA theories and shows the performance of the method is compared to existing algorithms such as ABC, GSA and Multi-article Swarming Cooperative Method.

The researchers of [15] suggest a HEEQA method for achieving a balance among equipment power. The message authentication code underlay settings are then adjusted to reduce energy usage in the systems. In Connected systems, maintaining QoS is a big problem, and maintaining the carbon cycle is critical to extending the sensor's life. Quant particle swarm optimization (QPSO) is used with an improved framework's evolutionary sort technique to accomplish that. The HEEQA technique improves energy consumption, thereby providing improved lifetime, speed, and supplies, according to the simulated results.

The authors of [16] suggest an unequal cluster of the period routing algorithm to solve the problem of unbalanced energy usage and delayed data transmission in WSNs. It is contrasted to several other algorithms. Simulation trials revealed that such an approach enhances system performance and balances the channel's energy usage, increasing the channel's life. The proposed method is especially well-suited to IoT systems that need low latency. Describes a data sources correlation algorithm that increases cognitive network bandwidth by combining data correlation analysis with device grouping [17].

The writers of [18] proposed a general IoT Data Streams cluster-based approach that uses the distribution of data to discover different categories identified in the stream of data. The suggested grouping technology's findings may be utilized as input for information processing, incident acknowledgment, and actual data stream analytics.

The researchers of [19] propose a new solution for edge devices with Connected systems called non-orthogonal multiple access (NOMA), which takes into account IoT device clusters and energy management in Hybridized NOMA systems. The complex clustering of IoT devices is addressed in the early phases to reduce network complexity and offset of improved channel conditions for IoT devices. In the second phase, Nash's balanced approach is used to address energy management based on electricity distribution. The simulation indicates that the proposed strategy can improve spectrum efficiency while interacting with other IoT systems and devices.

A Data Cluster Systems for Privacy and Availability (PADC), which uses k-mean methods and differentiated data protection through one central location to the other. Every iteration, the PADC algorithm multiplies each clustered value by the frequency of clusters, assisting in the calculation of the different positions among pieces of data for more precise input numbers. When compared to previous differentiated methods in terms of security, the suggested scheme improves the availability of sufficient bandwidth while maintaining the same level of privacy, implying that the suggested PADC scheme surpasses previous smart IoT electric grid solutions [20].

Based on the foregoing explanation, this can be stated that, although there are so many CH selection systems available, they all consume a great deal of energy. To solve this problem, a hybrid WOA-SA method is applied to minimize power consumption in the IoT network by selecting the best CH.

3. IoT WSN Adaptive CH Control

Many sensor networks make up an IoT network, each with limited storage and high energy consumption [21-23]. Because these units are constantly generating data, the batteries should be used more often. The lifespan of a system is shortened when energy usage is higher. One of the strategies of energy optimization is to select the best CH. Clustering is a process for dividing sensors into subgroups and assigning a leader from each grouping given a set of criteria. Cluster is known as subgroups, while CHs were known as facilitators. Cluster aids in the efficient use of internet services, network congestion control, packet forwarding, energy consumption, and life of the network management. Transmission cost inside the clusters, sensing power, and node distance from the BS are among some of the characteristics utilized to choose the optimal CH. The cluster nodes will transmit the information to their CH following picking the best CH. The data gathered would be sent to centralize BS via CH.

In this work, we examine C groups, represented by Ci, with i = 1, 2,3, 4..., N. Every cluster has X members, represented by Xi, with i = 1, 2,3,4..., M. TCH stands for the total number of CHs. Only the TCH that has been picked can connect with the IoT core satiety. Selecting the wrong CH for an Internet - of - things WSN which results in a life improvement became a difficult challenge.

3.1 Fitness function

CH is selected in classic WSN depending on characteristics such as distance, latency, and energy. We must focus on additional factors like power & temperatures even though we are combining WSN with IoT [24]. As a result, to optimize network performance and net longevity, the CH is chosen based on even a cluster having strong power and high load, as well as latency, length, and heat. The fitness value, which would be represented in Equation (1), must be maximized to increase the channel's stability and reliability.

$$FF_x = \delta * FF_{Temp} + \sigma * FF_L + \vartheta J FF_E + \rho(1 - FF_A) + \alpha(1 - FF_D) \text{-----------------} (1)$$

Where $\delta, \sigma, \rho, \alpha$ the biased parameter..

In the subcategories that follow, the statistically modeled estimate of the five variables established in this study is discussed.

3.2 Calculation of power

In IoT systems, the power spent in a single channel may be divided into two parts. The very first element is the power used by all Power Amplifiers (PA), and the other is the power used by the other Circuit Blocks (CB). For each connection, the power consumption, E, is calculated by using the following:

$$E = PA + CB \text{ -------------------- } (2)$$

IoT node energy can indeed be replenished. The power of an IoT node was originally E0. The packet must be transferred to a CH by each node in the network. Both CH, as well as the node, lose energy when transferring messages from the x^{th} node to the y^{th} CH. The hardware for the transmitter and receiver is present in each IoT device. The power evaporates in the form of a transmission and reception when the user transmits or transmits information. The transmitter's heat transfer is a type of energy amplifier known as radio circuits, whereas the recipient's heat transfer is also caused by radio electronics.

Power can be dissipated in 2 directions. The first one is when the user transmits m byte of memory to the CH specified in Equations (3). Whenever the CH gets m tb of memory from the base station, the heat transfer is shown in Calculation (5).

$$E\ [A_N^a] = \left[E_{energy} + m\right] + \left[E_{fes} * m\right] \left|\left|D_N \quad - D_{CH}^n\right|\right| - - - - - - - - - - - - - - - -(3)$$

Where,

$E\ [A_N^a]$ - Normal mode energy consumption
E_{energy} – Energy

E_{fes} - Free space

$A_N^a - A_{CH}^n$ - the distance between normal mode and CH

$$E_{energy} = E_{Transmitter} + E_{AD} - - - - - \quad (4)$$

$Where, E_{AD}$- Aggregation of data energy

$$E(A_{CH}^n) = E_{energy} * m \text{ ---------}(5)$$

When transmission and reception, the capacity both in regular nodes and the CH should be adjusted. The calculation indicates the current power availability in the network coordinator after transferring the data to the Control (6). The equation gives the current power accessible in CH following getting data from the base station (7). The information is sent to the CH by the normal node till the node's power isn't negative. If the energy of a node falls to zero, it is referred to as a dead node. The equation expresses the objective functions for energy (8). Another of the performance characteristics used to identify the best CH is efficiency [25]. To be selected as CH, the node's energy must be sufficient.

$$E_{D+1}[A_N^a] = E_D[A_N^a] - E_D[A_N^a] \quad \text{---------------------(6)}$$

$$E_{D+1}[A_{CH}^n] = E_D[A_{CH}^n] - E_D[A_{CH}^n] \quad \text{------------------------(7)}$$

$$FF_E = \frac{1}{n}\{\sum_{a=1}^{n} E(A_n^a)\} + \frac{1}{T_{CH}}\{\sum_{a=1}^{CH} E(A_{CH}^a)\} \quad \text{--------- (8)}$$

The performance index of the range from sink node to IoT BS is theoretically demonstrated by range calculation Equation (9). To select the optimal CH, the range among clusters and the IoT BS must be kept under control.

$$FF_{Dist} = \sum_{a=1}^{n} \sum_{x=1}^{T_{CH}} \frac{||A_N^a - A_{CH}^x|| + ||A_{CH}^x - A_{BS}||}{M*N} \quad (9)$$

$||A_N^a - A_{CH}^x||$ and $||A_{NCH}^x - A_{BS}||$ are distance between normal mode with CH and CH with IoT respectively.

M and N denote a range of dimensions in meters.

3.3 Calculation of the latency

The latency must be as little as possible while choosing the optimal CH. The delay will be between 0 and 1 milliseconds. Because the latency is determined by the number of nodes in the cluster, the number of nodes in a cluster must be kept to a minimum to reduce the delay. The equation shows the mathematical fitness function of the delayed transfer between Connected systems and CH [26]. The fraction is the highest transmission from a CH to the BS, while the denominator is the maximum set of neurons.

$$\mathrm{FF_A} = \mathrm{Maximum} \sum_{\mathrm{n}=1}^{\mathrm{T_{CH}}} \mathrm{CH_n}. \quad (10)$$

4. The WOA algorithm

WOA is a heuristic approach that is influenced by the environment [27]. This technique was designed depending on humpback commercial whaling habits. The bubble-net feeding technique is a whale assault style in which bubbles are generated in a ring from around the victim. There are two stages to this process. Attacking Prey, encircling Prey. Whales have a distinctive foraging habit that employs two strategies. One would be the uptrend, in which whales dive 12 meters below the surface and begin generating spirals of bubbles around their prey. Loop catch, natural selection to increase, and looped corals are the 3 parts of the second method.

4.1 Surrounding the prey

The humpback attempts to locate its meal and afterward surrounds it. The whales think that the present best outcome is target food so alert other searching whales to shift their positions towards the target food. Equations (11) and (12) depict the surrounding prey process [28].

$$L = |\, Y.Q^*(m) - Q(m)|. \tag{11}$$

$$Q(m+1) = Q^*(m) - X.L \tag{12}$$

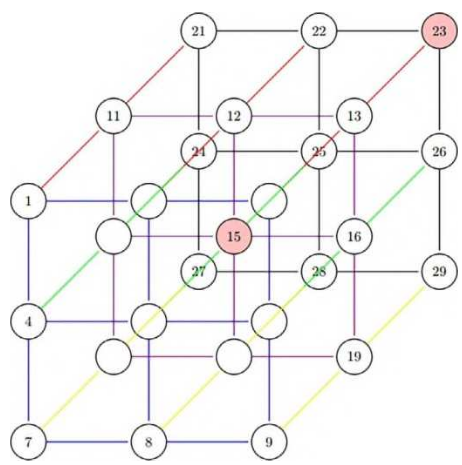


Figure 2: The best solution for vector position

Where,

X, Y denotes vector coefficient
m – Iteration position
Q* - best solution for vector position
Q – vector location

$$X = 2x\,\delta - x \tag{13}$$

$$Y = 2.\lambda \quad (14)$$

4.2 The assault of the bubble-net

There are two ways to assault a whale shark using a bubble net. The decreasing circumferential method and spiraling update are the first two approaches. The humpback employs a few of these two tactics to attack its food. The chances of catching prey using these methods are about 50%.

Approach with a decreasing circumferential effect. Now, the quantity of "x" begins to decrease from 2 to 0, affecting the value of X in Equation (13). X is a special variable in the [x, x] range. Figure 3 shows the variety of integer variables for X in the region of [1, 1]. Helix upgrading is a method of updating that uses a spiral. The equation is used to compute the distance between the whale and the target food in this method [29].

$$Q(m+1) = L.e^{pr}.\cos(2\pi h) + Q^*(m) \text{-----------------------} (15)$$

Where, L=|Q*(m)−Q(m)| is the optimum distance between whale and food.

When a whale shark spots prey, it swims around in a very swirly shape or a decreasing circle. A spiraling form or a decreasing circle has a 50 percent chance of being chosen. The equation shows how to update the location of the whale to get the optimum answer [30].

$$Q(m+1) = \begin{cases} Q(m) - x.L \ \text{if } P < 0.5 \\ L.e^{pr}\cos(2\pi h) + Q^*(m) \text{if } P \geq 0.5 \end{cases} \text{---------------------} (16)$$

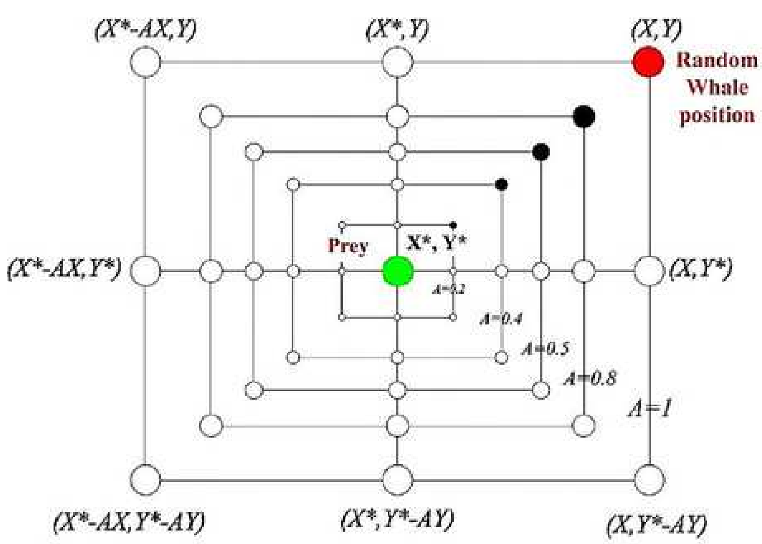


Figure 3: Probable finest solutions

4.3 Hunting for prey (exploration phase)

During this stage, the whales look for the best solution (prey) throughout the globe at random and shift their status in comparison to other whales. The value of X must be larger than 1 to compel its search process to go far away from several references whale worldwide. Equations (17) and (18) describe the general check for prey. WOA is explained in Solution 1.

$$L = |Y.Q_{rand} - Q| \tag{17}$$

$$Q(m+1) = |Y.SQ_{rand} - Q| \tag{18}$$

Algorithm: WOA with CH

Initialize the population of whale Q_i ranges from 1 to n

Calculate the strength of every agent.

while (m < mMaximum)

    for every searching agent

    renew x, h, X, P, Y values

    if P is less than 0.5

        if |x| less than 1

            upgrade the penetrating agent present location using Eq. 11

        else if |x| greater than or equal to 1

            chosen a penetrating agent as (Q_{rand})

            upgrade the searching agent position using Eq.18

        end if

    else if P greater than or equal to 0.5

        upgrade the searching agent position using Eq.15

    end if

end for

examine the strength of every penetrating agent and upgrade Q^* if optimum solution found

Calculate the strength of every agent

upgrade Q^* to get the optimum solution

m=m+1
end while
return Q^*

4.4 Simulated annealing

Simulated Annealing (SA) is also an optimization process based on a thermodynamics notion, namely how metals cool and then anneals. The 34 SA algorithm is used to choose the leading international optima from a set of local maxima. The optimization problem of a related optimal solution is used in this approach [31]. The road approach is comparable to this optimal solution. The optimum step for both the goal function will be picked in the hill-climbing approach, but a randomized movement would be selected in EA.

This will be approved if the selected randomized movement enhances the result. Otherwise, the method computes a decision with a chance of less than one.

4.5 In the IoT Network, a Hybrid WSO-SA Approach for CH Selection

Figure 4 shows the architecture of the proposed WSO-SA method for the CH selection process in an IoT network. A BS with clustering makes up the created virtual IoT network. Several endpoints, as well as a CH, would be displayed for each cluster. The information is sent to the CH from each node. The CH will compile the information gathered from the entire node and transmit it to the IoT BS. The combination WOA-SA method is utilized to find the optimal node for CH. A variety of loading, cost, and thermal operating conditions was evaluated while selecting the CH. The following is the code for the proposed framework.

5. Results and Discussion

MATLAB R2015a is used to simulate the CH choice in IoT. The information from the Xively Network infrastructure is being used in the model. Several performances, including temperatures, number of living nodes, loading, power, and cost function, were studied in this research to select the optimal CH. The algorithm relies on a 100 m x 100 m area. The IoT BS is supposed to have been at the heart of the study region. The remainder of this section compares the suggested performance of the model to existing techniques such as the Artificial Bee Colony (ABC) method, Gravity Algorithm to compute, and AGSA method.

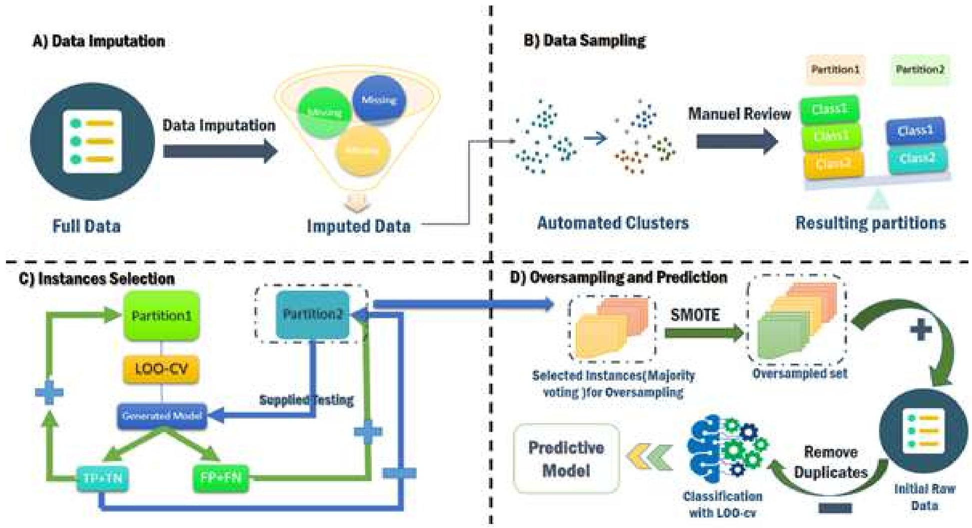


Figure 4: Proposed methodology

5.1 Temperature measure is used to evaluate the performance

Figure 5 depicts the suggested designer's overall performance of the "temperature" measure. For all techniques, the temperature mostly on IoT devices appears to be lower at first. The temperature competitive advantage arises as to the number of cycles increases for all techniques. Figure 5 shows that the temperature produced by all of the techniques is almost identical at first. However, after 1800 cycles, the heat created either by the suggested technique is significantly lower than that produced by earlier studies.

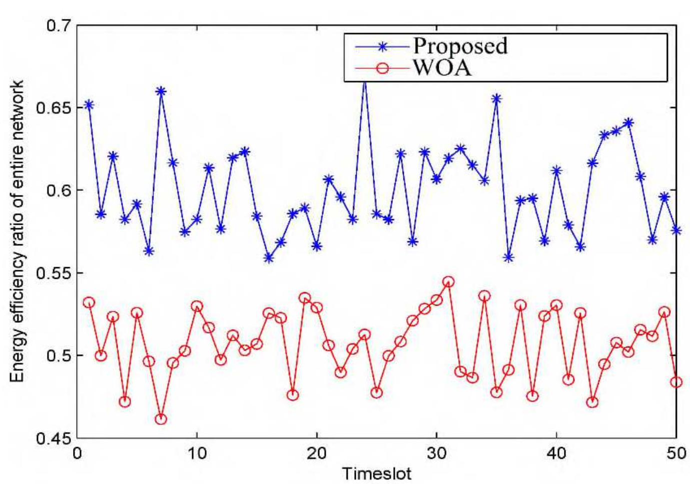


Figure 5: Energy efficiency ratio performances

5.2 The quantity of alive nodes is used to assess project

The effectiveness of the proposed scheme to existing models depending on the number of the sensor node. The entire node remains alive throughout modeling in the first 1000 cycles, as shown in this diagram. With all designs, the number of regular links steadily decreased following 1000 cycles. Current models have no living links beyond 1700 cycles. However, after 1700 cycles, the proposed method contained about 20 alive links. As either a result, the suggested approach extends the lifetime of the network by maintaining additional nodes alive until the final cycle.

5.3 Evaluation of the effectiveness depending on the load measurement

The effectiveness of the suggested system that is based mostly on the loading of CHs is shown in Figure 6. The efficiency of the IoT system would be best if the load is evenly spread among several CHs. It can be seen from this diagram that the suggested model evenly spreads the load among all CHs. In all rounds, the suggested model optimizes the workload. As compared to existing algorithms, the burden on CHs is negligible even after 1500 cycles. The temperature generated by the sensor network would be lower whenever the strain upon this CH is lower. The IoT system consumes lesser energy with the help of all this and enhances the program's efficiency.

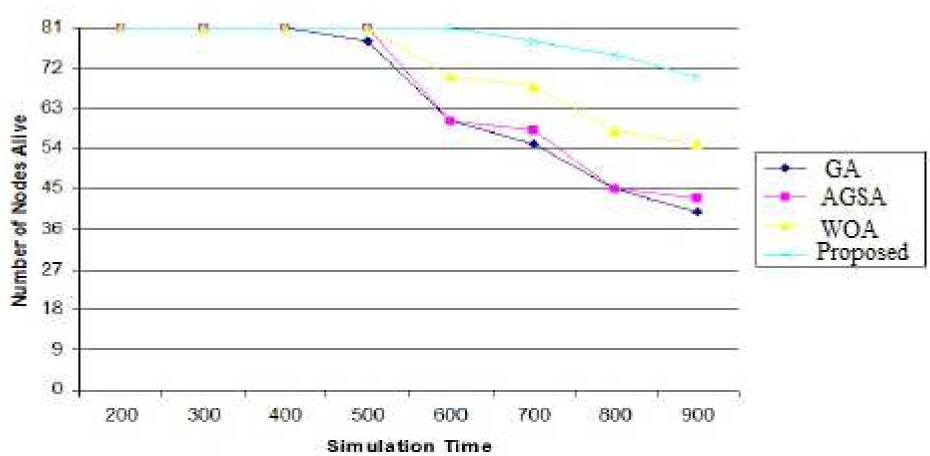


Figure 6: CH performance

5.4 Analysis and evaluation depending on the energy indicator

Figure 7 compares the results of the designed energy-based approach to that of other current models. For all simulations, the power of the network is assumed to be 0.5 J at first. The energy decreases as the number of cycles rises. The suggested model, when compared to current models, had more energy in the system iteration, as seen in the image. It will contribute to the channel's long-term viability.

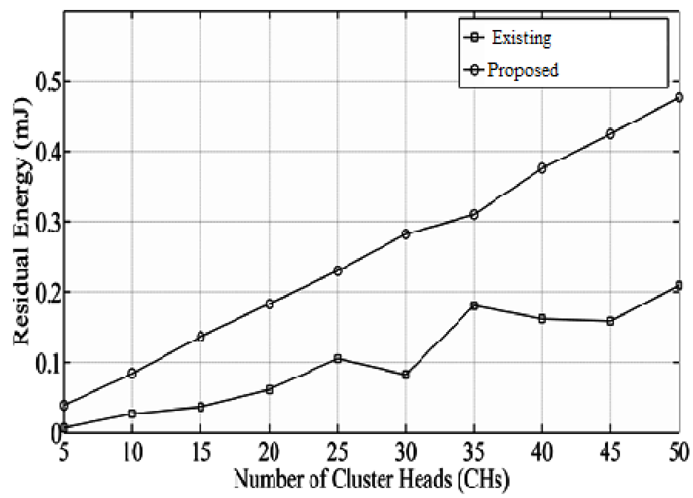


Figure 7: Energy metric performance

5.5 The cost function is used to assess project

The effectiveness of such a proposed approach based on a cost function is shown in Figure 8. The efficiency of a method is determined by the cost function. The efficiency of methods will improve significantly as the number of samples rises. The proposed approach exceeds the current methods in terms of converging, as shown in the graph.

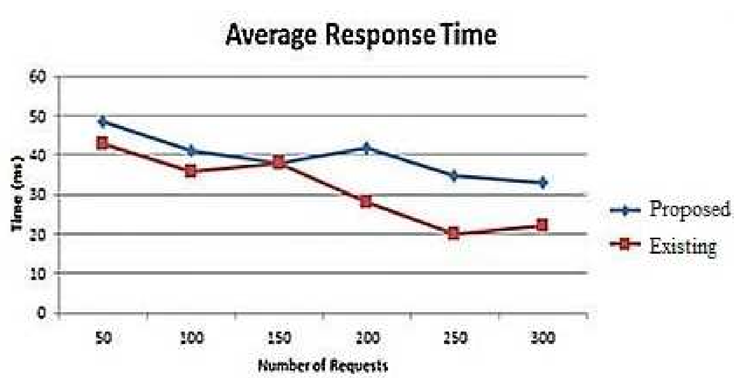


Figure 8: Cost Function Performance

In almost all of the metrics evaluated, the current platform outperforms the traditional approaches, as shown in Figures 5-8. Linear approaches, regardless of performance parameters, employ the blinded operators for exploitative reasons. The proposed algorithm, which works as an operation throughout the WOA-SA technique, guarantees that the blinded operators are substituted with such a search engine that uses the result as an origin point. Eventually, following focusing on one aspect searching, the improved result fills the role of the original. As a result, the WOA application's exploiting capability is improved by the evolutionary programming process. As a result, the modeled aging technique aids in the WOA's effectiveness in locating the best solutions. As a result, the proposed method outperforms current methods in terms of IoT system performance optimization.

6. Conclusions

Even though IoT has enormous opportunities in a spectrum of uses in the modern-day, there are several obstacles to overcome. Safety, power efficiency, transportation, hardware configuration difficulties, information network connectivity, and other troubles must be solved to improve the resilience of IoT. Researchers opted to focus on the optimized design problem in this study. To solve this problem, the current study employs a hybrid meta-heuristic method called WOA-SA to optimize the power usage of devices in IoT-based WSNs. The Xively IoT technology is utilized in this study to mimic an IoT network. The Internet of Things connection has gone through 2000 versions. Throughout this study, various performance measures including load, power consumption, number of living nodes, cost function, and temperatures were utilized to select the best CHs for IoT systems. The suggested method is then compared to several existing methods. The results of the experiments show that the suggested method outperforms the traditional methods. Numerous other performance criteria, including latency, node density, link lifespan, and so forth, might be evaluated throughout the latter to pick the best CH. In addition, the suggested work may be scaled by utilizing this technique in real-time systems with a large number of sensor nodes, and the energy usage of the whole IoT system is assessed in this study. Future studies may look at power management in each isolated network in an IoT system, and safety issues identified by multiple researchers like reference 33 could be used in the proposed model to solve security problems.

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Declaration:

Ethics Approval and Consent to Participate:

No participation of humans takes place in this implementation process

Human and Animal Rights:

No violation of Human and Animal Rights is involved.

Funding: No funding is involved in this work.

Conflict of Interest: Conflict of Interest is not applicable in this work.

Authorship contributions:

There is no authorship contribution

Acknowledgment :

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