A Framework for the Internet of Things that is Energy-Efficient and based on Swarm Intelligence

Tejraj[1], Manvi Chopra[2], Yogesh Kumar[3]

[1]Assistant Professor, Electronics and Communication, School of Engineering, DevBhoomiUttarakhand University, Chakrata Road, Manduwala, Naugaon, Uttarakhand 248007

[2, 3]Assistant Professor, Computer Science & Engineering, School of Computer Science & Engineering, DevBhoomiUttarakhand University, Chakrata Road, Manduwala, Naugaon, Uttarakhand 248007

[1]ece.tejraj@dbuu.ac.in, [2]ece.manvi@dbuu.ac.in, [3]socse.yogesh@dbuu.ac.in

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Abstract

In recent years, Internet of Things (IoT) technology has been created for use in a wide range of industries. The Internet of Things network is equipped with a great number of sensors that may collect information immediately from their surroundings. The sensing components of the network serve as sources by monitoring environmental events and transmitting vital data to the relevant data center. When the sensors pick up on the aforementioned occurrence, they transmit the data about the world to a central station. On the other hand, sensors have limited processing, energy, transmission, and memory capacity, which may have a negative impact on the system. These limitations may cause the system to malfunction. Our present research efforts are focused on finding ways to reduce the amount of energy that is used by sensors in the Internet of Things networks. The goal of this research is to identify the Internet of Things (IoT) network potential node that has the most potential to improve energy efficiency. Throughout this whole research, we present a fusion of techniques that combines the skills of PSO's exploitation with the capabilities of GWO's exploration. Specifically, this fusion would merge the two sets of capabilities into one. The essential idea is to combine the capabilities of the PSO to efficiently exploit prospective nodes with the capabilities of the Grey Wolf Optimizer to choose potential nodes in the most efficient way possible. On the basis of many performance measures, the suggested technique is contrasted with the conventional PSO, GWO, Hybrid WSO-SA, and HABC-MBOA algorithms.

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1 Introduction

In recent years, there has been tremendous development in the technology behind the Internet of things (IoT), and now there is an abundance of devices that make use of this technology. [1] The terms "Internet" and "Things" refer to a worldwide network that is linked and founded on sensory, communication, networking, and information processing technologies. This network is referred to as the "Internet of Things." Every single piece of hardware, from kitchen appliances to autos to air conditioners and thermostats, now has the capability to connect to the internet. These gadgets encompass anything from common household appliances to complex manufacturing equipment[2]. The new wireless sensing technologies have significantly enhanced the sensory capacities of devices, expanding the fundamental concept of the internet of things to include ambient intelligence and autonomous control [3].

CISCO and Qualcomm (loE) are two companies that have utilized the phrase "Internet of Everything" [4]. The word CISCO may refer to a variety of different things. People, data, procedures, and objects all come into play.
IoE is built on what are known as the "four pillars." The expansion of business and industrial activities is another way in which the IoE makes people's lives better. IoE has the ability to gather and analyze data from the billions of sensors that are attached to it, and then use that data to improve "automated and human-based processes." The use of IoE to assist in the fulfillment of national priorities, ecological responsibility, and socioeconomic goals is another benefit. Other advantages include the use of IoE. [5]

On the Internet of Things, embedded apps now have a place to call home. The vast majority of these applications are dependent on highly embedded systems, which are required to operate using limited energy sources such as batteries or energy harvesters [6]. There is a significant amount of challenge involved in satisfying the application's energy needs [7]. The internet of things network is composed of sensor nodes that are both wireless and inexpensive. It is difficult to do normal maintenance on a WSN because of the very high number of sensor nodes, such as changing the batteries [8]. The energy source of the node, which is often a battery, loses its charge at a more rapid rate. As the distance between the nodes rises, the amount of power that is used also does. In order to solve the problem, this research takes a Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) approach, both of which are based on Swarm Intelligence [9][10]. We integrate two methodologies by exchanging a particle from the PSO that has a low probability for a particle that has been somewhat improved by the use of the GWO. This has a substantial influence on the amount of energy that is still available in the nodes, since traveling greater distances requires more energy. A hybrid model of PSO and GWO is built with consideration given to energy consumption and distance, and it chooses the best possible next node via an iterative process. In contrast to the greedy strategy, this one aims to reduce the distance between nodes and, as a result, increase the lifetime of the network.

Mirjalili[11] came up with the idea for the GWO approach, which is centered on the methodology of wolf poaching. Particle swarm optimization (PSO) and other optimization algorithms may not be the best choice for deployment in practical applications; GWO, which has fewer adjustable parameters and is simpler, may be a superior option. When used with high-dimensional nonlinear objective functions, the GWO, like other optimization techniques, has a number of drawbacks, including the fact that it is easy to become caught up in the local optima [12]. In addition, the increased convergence speed of GWO makes it more difficult to strike a balance between exploitation and exploration in terms of resource use. In this research, we make use of a hybrid model that combines PSO and GWO in an effort to circumvent these restrictions. The consistency of the PSO technique is maintained by our hybrid methodology, and the assistance of the GWO algorithm is used to facilitate exploration.

The full list of acronyms that appear in the text is shown in Table 1. The remaining parts of the paper are divided into the following sections: The discussion of the literary work may be found in Section 2. Examining the GWO-PSO is the focus of Section 3. The section titled "Section 4" contains an explanation of the energy-saving model. Section 5 contains the conclusion that was reached.

Table1.Acronymsandtheirmeaning

Acronym	Meaning
SI	SwarmIntelligence

IoT	InternetofThings
WSN	WirelessSensorNetwork
PSO	ParticleSwarmOptimization
ABC	Artificialbeecolony
GWO	GreyWolfOptimizer
CH	ClusterHead
pbest	ParticleBest
gbest	GlobalBest

The following are some of the scientific contributions that this study made:

• To carry out a comparative study of several energy-efficient PSO-based techniques in the Internet of Things.

• To develop and create a framework that is energy-efficient for the Internet of Things.

• To combine the functions of PSO and GWO in order to choose prospective nodes in an internet of things network more effectively.

1 Analysis of Previous Work

The construction of a model that is efficient in terms of energy consumption is now presenting the researchers with significant challenges. Researchers from a variety of academic institutions have been working on methods that are more efficient with energy to build an optimal model. As a consequence of their efforts, the lifetime of networks that use WSNs will be extended. In the next section, we will talk about how meta-heuristic techniques may be used in the energy industry.

In their paper, Devika et al. [13] suggested an energy-efficient clustering strategy for WSN (wireless sensor networks). In this essay, the author shows why SI (Swarm Intelligence) is a strategy for lowering energy usage and making networks more energy efficient, as well as how and where this technology may be used. The author found that, out of all the many SI methodologies, the PSO methodology was the most effective one. The SI algorithm is segmented into groups based on the social behavior of organisms such as insects, bacteria, birds, fish, and other animals; however, insect-based SI accounts for more than half of the work put into developing the algorithm. The author used a number of different SI-based WSN clustering approaches, including as ACO, PSO, and ABC, to decrease the amount of duplicate data that was present inside the clusters.

According to the findings of Alqattan et al. [14], the PSO is more dependable than the ABC. In order to test the Protein Structure Prediction, the author used the ABC approach in conjunction with the PSO algorithm. Several indicators, such as Colony size (S) [total number of working and observing bees], Swarm population size (N), S1 for Self-confidence, and Swarm-confidence for Swarm-confidence, are used to assess the effectiveness of two distinct algorithms (S2). The author shows, via the use of these different criteria, that the PSO methodology surpasses the Artificial Bee Colony technique in terms of Time, Average Number of Function Evaluation, and accuracy numbers by a margin of 70%, 73%, and 3.6%, respectively.

According to Rao et al., the increasing overload that occurs during the process of receiving and collecting data causes cluster heads, also known as CHs, in Wireless Sensor Networks (WSN) to use more energy.

[15] The author of this work presented a method for selecting cluster heads called particle swarm optimization, which was intended to improve energy efficiency. The fitness function, which considers factors such as the nodes' remaining energy, load, temperature, and aliveness, plays a role in the selection of CH. Because of this, the Cluster-head is selected such that both the speed of the network and its longevity may be optimized. CH is selected as the fitness function enhancer based on a high-energy node that has low load, latency, range, and powerful heat. This should be enhanced to boost the net-stability works and efficiency. In addition, Iwendi et al.[16] explain the fitness function to find the cluster head (CH) by utilizing,,,, and as weighted parameters. The computational parameters that are employed in the calculation of the fitness function are energy and.

(Computation of energy), "distance" (Computation of distance), "FFdelay" (Computation of delay), "temperature" (Computation of temperature), and "FFload" (Computation of load) (Load computation). The fitness function may be thought of as the accumulation of all of these values [17].

In [5], Vijayalakshmi et al.[18] discussed the Tabu-PSO model, which is a hybrid PSO and Tabu method to select the cluster head with the least power utilization rate in the cluster and to increase the flexibility to pick the CH in an IoT network by utilizing a hybrid heuristic approach. Both of these goals were accomplished by selecting the cluster head with the lowest power utilization rate in the cluster. Tabu's research was used to improve the ethnic diversity of PSO in order to avoid concerns associated with local optimality.

This was accomplished by increasing the number of clusters and improving the node survival rate. Their proposed approach significantly decreases the total packet loss rate by 27.32 percent and the average end-to-end latency by an average of 1.2 seconds. This is in contrast to the Low-energy adaptive clustering hierarchy algorithm and the Particle Swarm Optimization.

In addition, the author presents the GWO in [11], which is a revolutionary algorithm that is based on SI and is influenced by grey wolves. The performance of the proposed algorithm in terms of search, attack, avoidance of local optima, and convergence was evaluated with the use of twenty-nine different test functions. When compared to other well-known algorithms such as PSO[19], GSA[20], DE, EP, and ES, the author found that GWO produced remarkably competitive results.

In addition, the GWO, the ABC, and the AFSA are compared against one another by the author in [21] in terms of the duration and effectiveness of their respective networks. The author came to the conclusion that AFSA and ABC have a shorter network lifetime than GWO does. The GWO used less energy than the ABC and AFSA while operating in an IoT environment. Also According to the results obtained by the author, GWO has a throughput that is, to some degree, greater than that of ABC and AFSA.

In addition, the author provides a one-of-a-kind hybrid method in [21] that combines the searching capacity of the GWO with the exploitative ability of the particle swarm optimization (PSO). The author combines two methods by exchanging a particle from the PSO that has a very small probability for a particle that has been somewhat boosted by employing the GWO. According to the results of the study, the hybrid technique effectively integrates the two algorithms and surpasses all of the other approaches that were evaluated.

Table2. ComparativestudyofPSO-basedframeworksincutting-edgeIoTindustries.

Author	Year	Contribution	Techniques used	Merits	FutureScope	PerformanceMetrics
Rao et al.[15]	2016	IoT networkCH selec-	PSO-ECHS,	Energycon-sumption rateisreduced	Workforheterogene-ousnetworks.	Energyconsump-tion,networklif

		tionconfig-uration				etime,packetsreceiving,
Vijaya-lakshmi etal.[18]	2021	WSN's effectiveclusterheadselection	Tabusearch(TS),PSO	Reducetheaveragepacketloss	Improvedbyintegrat-ingfireflyandTSmethods.	Alive nodes,Averagepacketloss,Networklifespan.
Ahmetetal.[22]	2018	Optimiza-tion ap-proach us-inga hy-bridizedmethodolo-gy.	PSO,GWO	Hybridtech-nique convergestomoreopti-mumsolution with least itera-tions.	Thehybridizationprocessbetween PSO and GWO willimprovethesearchperformance.	Energy,Throughput
Kauretal.[23]	2018	Energy-efficienthybridme-taheuristicapproachfor sensornodes	AntColonyOptimiza-tion (ACO),PSO	Enhancesnet-work lifetime byconservingtheenergy	Improvethenode'sperformance.	Networklife-time,Through-putResidualenergy
Rastogietal.[24]	2021	Optimisa-tion ap-proach inWirelessSensorNetw	PSO,ACO	In the context ofNetworkLon-gevity,thisgivesthebestperformance.	Toworkbetterinvirtuallyalloftheperformancefactorsmentioned,useavariety of alternativecomputationalintel-ligenceapproaches.	Alive node, Dead node, Throughput,Remainingenergy.

		ork				
Sundara murthye tal.[25]	2020	Optimiza-tion ap - proach fo rprediction ofArthritis	PSO,GW O	Enhancesener-gy efficiency ofnodes	Proposeahybridmeth odologytoenhancen oderelia-bility.	Network'slifeti me,Throughput ,Averageener-gy consump-tion

The comparative research conducted by a variety of authors on a number of IoT frameworks and models is outlined in Table 2, which can be found here. The authors made some educated guesses about the model's analysis, approach, strengths, and disadvantages, as well as its quality measures. Within the framework of the model, a wide variety of characteristics were used to classify metaheuristic methodologies and approaches.

1 Optimization Using a Particle Swarm (PSO)

The PSO idea was first presented to the public in 1995 by John Kennedy and Eberhart [19]. PSO stands for "population-based stochastic optimization" and refers to a methodology. It is composed of a swarm of particles (fishes, birds, and so on) that are moving around a search region in search of possible solutions to complicated problems. Every single person has a velocity vector and a location vector that, when combined, offer a potential answer to the problem. The velocity in this context refers to the amount of time spent processing.

or coverage, and the position held here corresponds to the rank of a test case during the process of testing. In addition, every particle has a little memory that not only recalls the best position it has ever held for itself, but also the greatest position it has ever attained on a global scale as a result of its interactions with the particles in its immediate environment. The Particle Swarm Optimization algorithm took what it had learned from the scenario and applied it to the many optimization problems that it encountered. Every possible solution is represented as a "bird" in the Particle Swarm Optimization model's solution space. A "particle or individual" is what some people call this thing. Along with velocities that direct their flight, every person contains values of their fitness that are evaluated by the fitness function in order to maximize them. Throughout the region of the solution, the person will follow the individual who is now ideal. PSO begins its search for the best possible answer by generating a collection of random solutions, which it then iterates over generation after generation. Every cycle, a comparison is made between the two "best" values, which results in the reorganization of each particle. At this point in time, the first alternative (fitness) is the most efficient choice. (In addition, the importance of physical fitness is preserved.) This particular number has been given the designation pbest. Another value that is recorded by the particle swarm optimizer is called the "finest" value, and it is the best value that any individual member of the swarm has attained so far. The "gbest" value, which stands for "global best," is the value that is considered to be the greatest. The overarching idea of Particle Swarm Optimization is shown in Figure 1.

PSO places a larger emphasis on maximizing WSN lifetime than other algorithms, such as GA[26], since it has an edge over these other algorithms. It is also easier to use, has the capacity to avoid reaching local optimal solutions, and converges more quickly. These are only some of its many benefits. Its fitness function takes into consideration the unused energy of nodes in addition to the distance between them. As a result, the WSN is provided with an optimal route as a result of the PSO's capacity to avoid local optima. PSO is used for a variety of purposes, including the positioning of nodes, the selection of CHs, and the formation of clusters. PSO implementations are supposed to help with energy management by cutting down on the amount of money spent on energy for each activity, which should lead to an increase in node longevity.

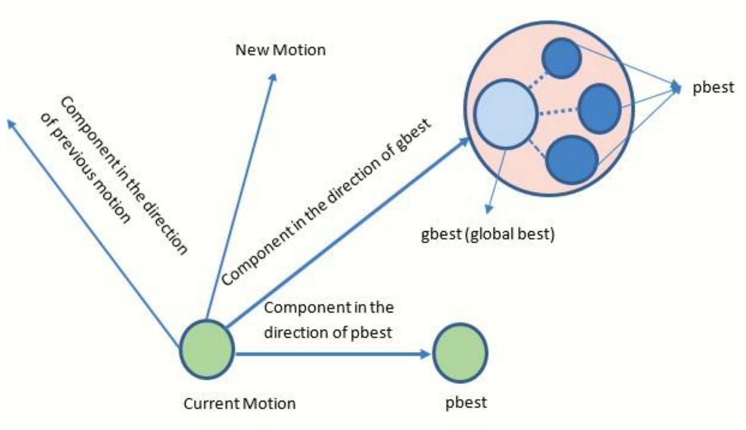

Fig.1.DiagrammaticalrepresentationofPSO Pseudocode of PSOStep1: Begin

Step 2: InitializationFor eachparticle

a) Set the initial location of the particles to have a uniform distribution

b) Establish an initial velocity for the particles.

Finishing Up Step 3: Conduct an Individual Fitness Function Evaluation for Each Person

If the fitval (fitness value) in the past is higher than pbest, then the statement is true. Change the value that is currently being used to the new pbest value.

End If End For Choose the person who among all the people has the best fitval (fitness value), then that person will be your gbest.

For each person, make the necessary adjustments based on Eq-1.

Keep the as indicated by Eq-2's End For variable up to date until the halting requirements are met. End Begin

After determining the two values that should be used, the person or particle will use the equations (Velocity Update equation) and (Position Update equation) to make the necessary adjustments to its velocity and location (Position Update equation).

The equation for the "Velocity Update"

{Position Update Equation} Where I refers to the particle index

w: learning components pertaining to the inertial coefficient Random variables : The velocity of the particle with respect to time t: Position at time t of the particle now being considered: The optimum solution for the particle if given time t is: The best possible global solution as of time t

3.1 Optimizer of the Grey Wolf

The GWO algorithm was first described in Mirjalili et al. [11]. The GWO has been impacted by the social structure of grey wolves as well as their hunting habits. The results of the tests showed that it is capable of addressing a wide range of conventional engineering design issues, such as those involving spring tension, welded beams, and so on, and that it performs very well in doing so. Leader of the grey wolvesship served as a motivating factor in the development of the GWO algorithm. The grey wolf is the most powerful predator that exists on the face of the earth. There are four distinct types of grey wolves that make up the leadership system. These are the alpha, the beta, the omega, and the beta.

In the GWO algorithm, the response that is considered to be "best" is shown by "alpha" wolves. The population considers beta () and delta () wolves to be the second and third best options, respectively. The Omega () wolves provide the best opportunities for finding a solution. The GWO system operates on the presumption that alpha, beta, and delta wolves are the ones responsible for hunting, with omega wolves following in their footsteps. The following is a rundown of the three most important facets of grey wolf hunting: (1) Pursuing the target, gaining ground on it, and drawing near to it in order to attack. (2) Pursuing, encircling, and tormenting the victim until it finally comes to a full standstill in its movement. (3) Sneaking up on the victim and ambushing it by surprise.

The formula may be broken down as follows:

The number of iterations is denoted by the letter t, the location of the prey is denoted by the letter Xp, and the position of a grey wolf is denoted by the letter X. While r1 and r2 are used to provide random integers, a and C are used to define vector coefficients. The fitness function for alpha, beta, and gamma groups is denoted by the letters D, D, and D respectively.

Grey Wolf Pseudocode, an Optimization Algorithm Step 1: Begin

The second step is to set a, C, and t equal to one.

Step 3: Determine the level of fitness possessed by each member in the population.

a) X is the person who has the highest value of fitness

b) X stands for the person who has the second best fitness value

c) X stands for the person who has the third best fitness value

While (i<Maximum itr)

Each individual's location is updated using the equation X (t+1) = (X1+X2+X3)/3, where X1, X2, and X3 represent the position vectors of the,, and wolves, respectively.

End Please update t, a, and C.

Determine the physical condition of each person. Update Xα, Xβ, Xδ i=i+1 End While Return X has been.

The fourth step is to return the best option.Step 5: End

2 Proposed Organizational Structure

According to the proposed architecture, which is shown in figure 2, an energy-efficient sensor network needs to be designed in the bottom layer. This is because the bottom layer is the only place where the amount of energy that sensor nodes consume can be reduced before it is transferred to the middle layer.

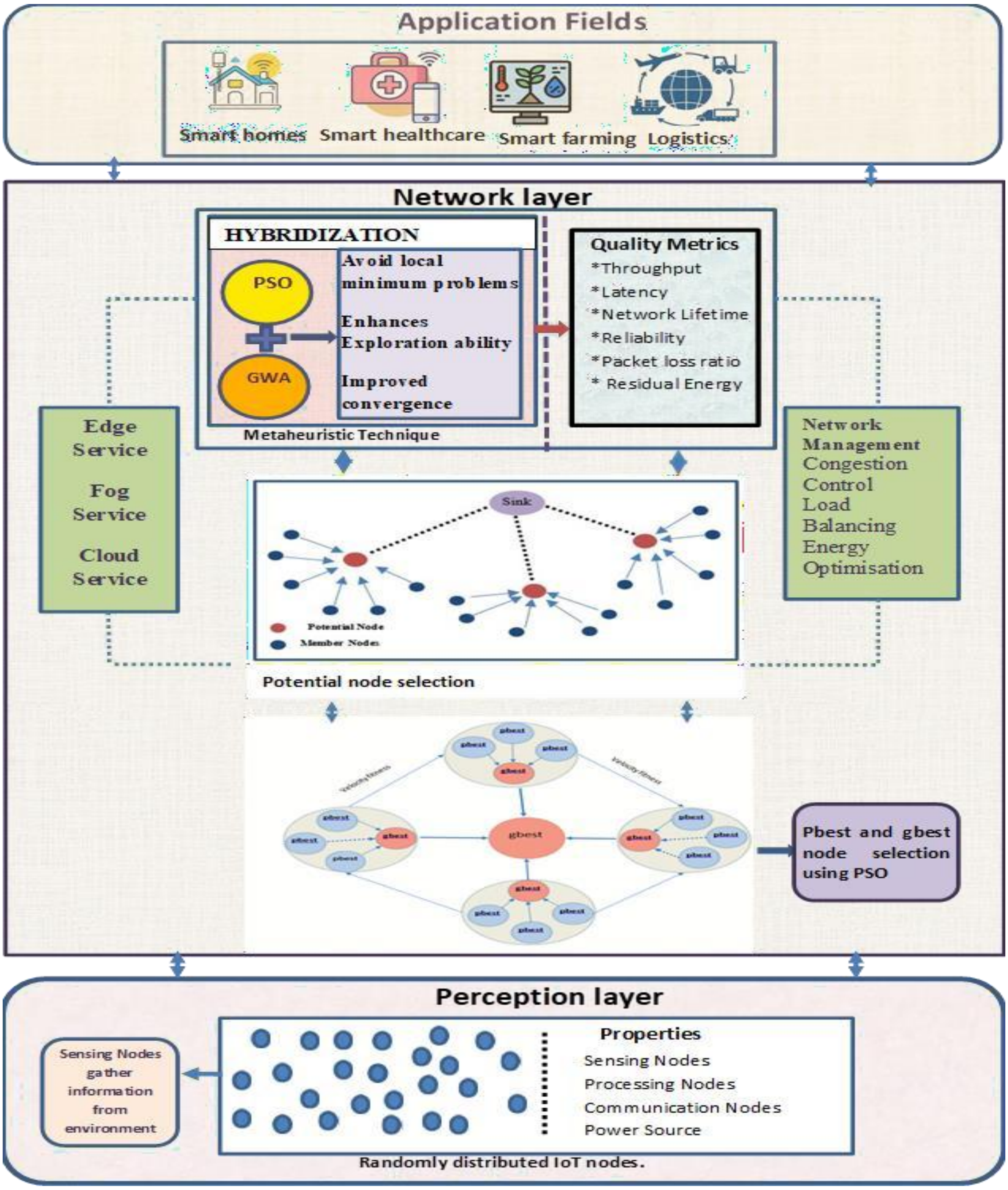

Fig.2.SwarmIntelligencebased energy-efficient frameworkusingPSO-GWOin IoT.

The core functionality of the Particle Swarm Optimization and Grey Wolf Optimization algorithms has not been changed in the process of developing our hybridized suggested technique, which we refer to as PSO-GWO. The PSO technique may be used to solve almost any problem that arises in the real world. However, there need to be some kind of mechanism that cuts down on the chances of the Particle Swarm Optimization algorithm being fooled into settling for a solution that has a local minimum. The Grey Wolf Optimization algorithm is used in our suggested method to assist the Particle Swarm Optimization algorithm in order to lessen the chance of the algorithm collapsing into a local minimum. This is accomplished by using the Particle Swarm Optimization algorithm. As was said before, the PSO algorithm directs some particles to random locations, where there is a remote possibility that they would escape local minimums. In a word, these avenues might end up taking us in a direction that is different from the global minimum. To get over these issues, the exploration capacity of the GWO algorithm is utilized to direct certain particles to GWO-enhanced places rather of random sites. This is done so that the system can perform its job more effectively.

Therefore, an efficient use of energy may be achieved by putting into practice the hybrid technique described above. Because the hybrid model of PSO-GWO has the potential to enhance the optimization method, it also has the potential to increase energy efficiency by reducing the amount of energy that is used. The hybrid model is helpful in evaluating the optimum strategy to achieve increased throughput while simultaneously reducing the amount of energy used. The Internet of Things architecture is used as the foundation for the model that has been suggested.

• The physical layer has a variety of nodes that are spread out over the region geographically. The perception layer is below the physical layer. Each of the intelligent devices that are able to function on the bottom layer is assigned its own unique identity. Intelligent devices that are located on the bottom layer are characterized by having a detector, a processing unit, a transceiver unit, and a valid power supply. Many different types of smart gadgets, each with its own unique set of requirements, standards, and technology are now being produced by various manufacturers.

• Network Layer: The middle layer, often known as the core layer, is where the actual data transfer happens. After being gathered at the perception layer by sensor nodes, the data is then sent to the network layer, where it is processed. The network layer is divided into three sections, which are as follows:

1. The selection of the pbest and gbest nodes: The pbest and gbest solutions, respectively, are the particle best and the global best solution. The PSO method is used in order to choose the pbest and gbest nodes. After determining the two values that are optimal, the particle will next alter its velocity and positions by using the particle velocity update equation, which is denoted by eqn 1, and the particle position update position equation, which is denoted by eqn 2, respectively.

2. The selection of potential nodes in each area for optimal energy efficiency During this step, aggregates sensor nodes are chosen, and potential nodes (PNs) are selected for all of

the clusters in each region. The information that has been gathered from each of the nodes will be combined by the prospective node, and then it will be sent to the node that serves as the basis for the Internet of Things. A PSGWO approach is used so that the potential node may be determined.

3. Achieve the optimum level of performance and solution metrics: A PSO model is utilized in conjunction with GWO in order to find the optimal solution. By using the exploration capabilities of the GWO methodology, the PSO method will be avoided from being stuck in local minimums, which will allow for the achievement of an optimum solution. The amount of load, the number of live nodes, the quantity of energy, the length of time the network has been operational, and the throughput are the performance measures that are used to choose the prospective node.

• Application Layer: The services offered by the applications layer are beneficial to a wide range of users, including mobile consumers, enterprises, and large organizations. It is the layer that has the highest possible user interaction. The application layer is where the actual communication begins and also where it is reflected.The cost function may be evaluated based on quality standards like latency, node lifetime, and residual energy.

Conclusion

In spite of the fact that the Internet of Things has enormous promise in a wide range of applications in the present day, there are a number of obstacles that need to be solved. To make the Internet of Things more resilient, a number of problems need to be resolved, including those pertaining to privacy, energy optimization, networking, concerns over hardware setup, and congestion in data networks. In this particular investigation, we have decided to center our attention on the challenge of energy optimization. In order to overcome this problem, the authors of this research developed a hybrid metaheuristic framework that is based on PSO-GWO to decrease the amount of energy that sensors in IoT networks use. The fact that there are fewer parameters to adjust is perhaps the most significant benefit of PSO. PSO achieves the best possible outcome via the interaction of particles; yet, it converges at a pace that is rather sluggish to the global optimum through the use of a high-dimensional search region. PSO is hybridized with GWO's exploration capabilities in order to circumvent this challenge and prevent difficulties associated with local minima. This research takes into consideration a number of performance criteria, including as energy consumption, network longevity, the number of live nodes, temperature, and throughput, in order to choose the most promising prospective node for an Internet of Things network. We will analyze the performance of the proposed method and compare it to the performance of existing meta-heuristic approaches such as PSO, GWO, Hybrid WSO-SA, and HABC-MBOA algorithms. These evaluations will be carried out with the assistance of a variety of simulations.

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