**Throughput Comparison for Improving Data Optimization using Artificial Bee Colony (ABC) Algorithm with Dynamic Technique**

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**Abstract**:

In the acquisition model of bees, where clustering is a suitable strategy to give a better path that doesn't cause any difficulties when transferring data, the artificial bee colony algorithm may be an efficient optimisation method. Additionally, clusters have a great deal of similarities among themselves but less among one another. The typical optimisation strategy is ineffective for handling huge dimensional data. In order to create a preliminary population of paths linking the source and destination nodes, this study proposes Throughput Comparison utilising Artificial Bee Colony (ABC) Algorithm with Dynamic Technique for Improving Data Optimisation Technique. Therefore, to choose a food source The ABC algorithm's artificial bee condition consists of worker bees connected to specific food sources, spectator bees observing worker bees' movements inside the hive to choose a food source, and scout bees searching for food sources at random. The throughput demonstrated in this study is superior to that of FANET-GSO, IGSO, UCRA-GSO, and ACI-GSO Techniques.

**Keyword:** Artificial bee colony algorithm, dynamic technique, data optimization, wireless sensor network, throughput, better route.

**1. Introduction**

Wireless sensor networks (WSNs) may self-organize an enormous number of minute sensor nodes with little battery power [1]. Wireless sensor networks (WSNs) may self-organize a massive number of small sensor nodes with little battery power. Despite the constraints of radio range, the sensor nodes in the network are sufficient for facilitating packet transfer. In real-time scenarios, these sensor nodes can also find, monitor, and recognise actual objects [2]. This sensor network consists of an infinite number of sensor nodes that can connect both with one another and with an external base station in order to provide reliable data dissemination [3]. There are a number of desirable qualities that wireless sensor nodes can have, such as cheap cost, small size, high compute power, simplicity of communication across short distances, and various functionalities for data processing, routing, and sensing [4]. It is used for data aggregation and sensing jobs. Particularly for sensor devices, it might be difficult to recharge them in unfavourable situations when they are ignored. The pressing issue of energy conservation of sensor nodes in a hostile environment must be addressed in order to extend the network's lifespan cost- and efficiently [5]. Several research approaches have been published in the literature to help sensor nodes conserve energy so that the emphasis may be on extending the network lifetime [6]. The sensor nodes' constrained energy, memory, calculation time, and computational capabilities, however, pose significant problems that degrade the network's performance. Furthermore, the network's capacity to properly use clustering and the amount of resources available are both essential for its endurance. A workable clustering routing protocol is broken down into three phases: cluster setup phase, cluster heads (CHs) election phase, and data transmission phase. This is a viable technique to reduce WSN energy usage. The sensor node groups in the detection zone arrange into clusters of varied sizes during the cluster setup phase. During the CHs election phase, certain nodes are selected as CHs according to a certain electoral process, while the remaining nodes serve as member nodes. The member nodes are responsible for gathering environmental data throughout the data transmission phase and delivering it to the CHS. The CHs transport the data to base stations (BS) of varied sizes after data collecting and processing.

For effective and efficient cluster management in this situation, clustering—the arrangement of neighbouring sensor nodes into groups known as clusters—is crucial. The cluster head (CH), which serves as an anchor in establishing connections between different cluster members as well as between cluster members and the base station, is a designated sensor node for each cluster. In other words, clustering is a grouping technique in which the cluster head nodes are solely responsible for transmitting the combined data from the sensor nodes to the base station [7]. The highest level of network design is anticipated to employ this clustering strategy to provide sensor nodes additional roles. The chance of enhancing efficiency and performing energy consumption optimisation is increased by WSN's clustering technique.

Wireless sensor networks (WSNs) have become active research fields as a result of their integration with sensor technology, distributed information processing, embedded technology, wireless communication, and microelectronic approach, among other things. Target tracking, environmental monitoring, national security, and underwater detection are just a few of the industries that commonly employ WSNs due to their benefits in low energy consumption and dispersed self-organization. Coverage is an important WSN issue because to its connection to connectivity, energy efficiency, and network reconfiguration. It focuses mostly on how to set up the sensors such that there is adequate coverage of the service area and that each location in the service area is kept under observation by at least one sensor. In order for WSN to operate effectively, there must be adequate coverage. The network's configuration and communication needs will be reduced with proper sensor installation, and resource management will be improved. In the field of robotics, path planning is a vital subject. It is a method for planning a path that avoids collisions in the presence of obstructions. Depending on the situation, the path should be optimised using a practical approach employing time, distance, or energy as the optimisation criterion. where path planning may be done in either a known or unknown environment. Since there is no documented map of the region, finding a way around might be challenging [8]. Despite having sensors and a GPS, robots cannot plan accurately in advance since the world is unpredictable. There are two types of path planning strategies: conventional and intelligent [9].The artificial bee colony approach was introduced for route planning for robots [10]. The major goal of the recommended strategy was to shorten the distance and travel time. [11] proposed the artificial bee colony technique for efficient path planning of mobile robots. The path is first constructed from the beginning point to the destination without colliding, and then it is optimised via the bee colony method. The original strategy was used to accomplish this. A global convergence approach based on a chaos-hybridized artificial bee colony was presented by [12]. The round-based network lifespan is used in this study to analyse a routing approach based on the Artificial Bee Colony (ABC) algorithm, whose preliminary performance findings were published in [13]. Similar to this, the ABC algorithm is enhanced by introducing a probabilistic selection scheme that, in place of the straightforward ABC algorithm selection [14], assigns probability values to viable solutions based on their fitness values and infeasible individuals based on their violations. This issue was addressed using Honey Bee Optimisation (HBO), which performs better in terms of energy efficiency parameters including scalability and network quality [16]. To reduce energy use, HBO looks for the most effective method at the lowest price.Whereas the Lion (FLION) clustering method, an efficient optimisation technique, was created for energy-efficient routing. As a result, this clustering method that uses a quick collection of CHs may be employed to increase the strength and durability of network nodes[17]. As a result, the energy clusters are built using the biologically inspired searching features of the ABC technique.This test also considers the model's complexity. The ABC algorithm is used to build the proposed routing scheme for time-based WSNs that provide data on a regular basis. The contribution of this paper is as follows,

* To use a dynamic approach to develop the ABC (Artificial Bee Colony) algorithm.
* To choose a food source, adhere to the ABC algorithm's broad framework (i.e., the employee bees, spectator bees, and Scout bees phases).
* Remember the finest solution attained so far.
* Use the dynamic technique's employee and observer phase while looking for data.

The reminder of the paper has been organized as follows: section 2 depicts the detail description of the proposed methodology; section 3 discusses the implementation results; finally, section 4 concludes the paper.

**2. Artificial Bee Colony Algorithm with dynamic technique:**

The foraging habit of honey bees serves as the basis for the ABC Algorithm. One type of swarm that may be observed in nature is the swarm of honey bees. To find food, this colony of insects employs its collective brain. The honey bee swarm has several characteristics, including the ability to exchange information, remember the environment, store and disseminate information, and make decisions on that knowledge. As a result, the Artificial Bee Colony algorithm's search space is limited and its sensitivity to the initial population construction is very high. This is one of the main reasons why the population of potential solutions moves the search space to a better-fitting region. The most important aspect of WSN is the network's longevity. In order to retain flexibility, hubs are often put together in groups led by a pioneer, also known as a bunch leader.In this study, a special ABC algorithm with a dynamic technique has been proposed for data transmission to the base station and support to the overall hubs in transmitting found data to target hubs in order to address the aforementioned issues. Because of the higher network performance, cluster heads (CH) utilise energy more prominently than generic hubs, as seen in Figure 1.

**Initial food source**

**Calculate the nectar**

**Determine the new food position for the employed bee**

**Calculate nectar**

**All onlookers distributed?**

**Memorize the position of best food source**

**Find the abandoned food**

**Produce new position for the exhausted food**

**All onlookers distributed?**

**Final food position**

**Determine the neighbor food source for the onlooker**

**Select a food source for the onlooker**

**No**

**No**

**Fig.1. Flowchart of the Artificial Bee Colony algorithm.**

The artificial bee condition in the ABC algorithm consists of scout bees that randomly search for food sources, observer bees that watch the employee bees' movements inside the hive to select a food source, and employee bees linked to specific food sources. Observers and scouts are also referred to as "jobless bees." All food sources are initially located by honey bee scouts. Beginning then, exploited honey bees and spectator bees begin mistreating food sources like nectar, leading to their eventual depletion. At that time, the worker bee that was preying on the depleting food supply transforms into a scout bee looking for new food sources. The upshot is that the worker bee that has run out of food becomes the scout honey bee. A food source's situation, according to ABC, relates to the quality of the related arrangement, and a food source nectar measure, to the quality of the associated arrangement (wellness). Due to each worker bee's entire dependence on a single food source, the number of honey bees employed is equal to the number of food sources (arrangements). For data gathering, the dynamic strategy employs both the employee and spectator phases. The approaches recommended are described in the next subsections.

**2.1.Population Initializationof data optimization using ABC Algorithm:**

ABC generates a population of SN solutions that are uniformly distributed, with each solution

$y\_{j}$(j = 1, 2..., SN) being a D-dimensional vector. The number of variables in the optimization problem is D, where $y\_{j}$ denotes the population's $j^{th}$food source. The following is how each food source is created:

$y\_{j}^{i}=y\_{min}^{i}+rand(0,1)(y\_{max}^{i}$-$y\_{min}^{i})$ ,$ ∀\_{i}=1,2,….D$ -------(1)

Where$ y\_{min}^{i}$ and $y\_{max}^{i}$ are the boundaries of $y\_{j}$ in $i^{th}$ direction.

Because it takes time to initialise with viable solutions and because it is sometimes difficult to generate a workable solution at random, the ABC algorithm does not consider the initial population to be viable. Algorithm 1 illustrates how initialization steps assign random values between the parameter's lower and upper bounds to the parameters of solutions.

**Algorithm1.Population Initialization procedure for ABC Algorithm.**

|  |
| --- |
| for **j=1 to**$\frac{S\_{n}}{2}$dofor **i=1 to D**do **Generate** $y\_{j}$ **solution**$y\_{j}^{i}=y\_{min}^{i}+rand(0,1)(y\_{max}^{i}$**-**$y\_{min}^{i})$**Where**$ y\_{min}^{i}$ **and** $y\_{max}^{i}$ **are the parameters lower and upper bound respectively.**endfor$failure\_{j}$**=0**endfor |

After initialization, the population is evaluated and exposed to repeated cycles of employed bees, onlooker bees, and scout bees searching for food. Algorithm 2 shows the Employed bee operation of the ABC algorithm.

**2.2 Employee Bees phase of ABC algorithm:**

Employee bees adjust the present solution depending on individual experiences and the fitness value (nectar amount) of the new solution during this phase. If the new food source fitness value is higher than the old food source's, the bee replaces the old one with the new one and discards the old. In this phase, the position update equation for the $j^{th}$dimension of the $i^{th}$candidate is as follows:

$w\_{ji}=y\_{ji}+ϕ\_{ji}(y\_{ji}-y\_{ki})$ ---------(2)

Where $ϕ\_{ji}(y\_{ji}-y\_{ki})$ is the step size $k\in \left\{1,2….S\_{n}\right\} and i\in \{1,2….D\}$ are two indices that were chosen at random.

**Algorithm.2.Employee Bees phase**

|  |
| --- |
| for **j=1 to**$\frac{S\_{n}}{2}$**do**for **i=1 to D do****Produce a new food source** $$w\_{ji}=y\_{ji}+ϕ\_{ji}(y\_{ji}-y\_{ki})$$**where k is a uniformly distributed random real number in the range [-1,1],** $S\_{n}$ **is a randomly chosen index that must be different from** $Φ\_{ij}$ **is a uniformly distributed random real number in the range [0,1].****endfor****Evaluate the quality of** $w\_{j}$**Apply the selection process between**$y\_{j}$ **and** $w\_{j}$**If solution** $y\_{j}$**doesn’t improve** $failure\_{j}=failure \_{j+1}$ **otherwise** $failure\_{j}=0$endfor |

An employee bee updates (3) the location of the food source (solution) in her memory based on the local knowledge and assesses the nectar quantity (fitness value, quality) of the new source (new solution). The perturbation on the location yji reduces as the difference between the parameters of the yji and yki decreases, as shown from Eq. (3). As the search comes closer to the best result in the search space, the step length gradually decreases. In light of this, the ABC algorithm decides by creating a new food source. As a consequence, the ABC method was altered to address certain optimisation issues using a dynamic strategy, where the structure of the algorithm drives the solutions to a working area in the process as it executes. After all the hired bees have finished the search process, they compute probability values and communicate their positions to the observer bees on the dance floor as well as information about the nectar and food sources they are using. These actions are explained in the algorithm below.

**2.3. Onlooker Bees phase of ABC algorithm:**

The onlooker bees phase begins once the employed bees phase is completed. During this phase, all employed bees in the hive share their fitness information (nectar) as well as their position information with the onlooker bees in the hive. Onlooker bees examine the available data and choose a solution with a probability$P\_{j}$, that is proportional to its fitness. The probability $P\_{j}$ can be computed using the given equations.

$P\_{j}=\frac{fit\_{j}}{\sum\_{1=1}^{S\_{n}}fit\_{j}}$ --------(3)

Where $ fit\_{i}$is the $i^{th}$ solution fitness value. As with the employed bee, the onlooker bee modifies the position in her memory and evaluates the candidate source suitability. If one's fitness level is higher than the previous one,the new position is remembered by the bee, whereas the old one is forgotten. Hence,the value of the parameter that exceeds its border is assigned to its boundaries in this method. The pseudo-code block of Algorithm 3 is in charge of the onlooker stage.

**Algorithm.3. Onlooker Bees phase**

|  |
| --- |
| **e=0,j=1**repeat**if random < p** then**e=e+1**for **i=1 to D** do**Produce a new food source for the onlooker bee**endfor**Apply the selection process between** $w\_{j}$ **and** $y\_{j}$**.****If solution** $y\_{j}$**doesn’t improve** $failure\_{j}=failure \_{j+1}$ **otherwise** $failure\_{j}=0$endif**j=j+1****j=jmod(**$\left(\frac{S\_{n}}{2}\right)+1)$**until e=**$\frac{S\_{n}}{2}$ |

The dispersion of all observers is followed by the identification of food sources that are no longer worth exploiting. After a predetermined number of cycles ("limit"), a solution is given up if it cannot be improved. In order to replace the food source that the bees abandoned, the scouts find a new one. To do this, a random location is created, and the abandoned one is then put in its place. As a result, Algorithm 4's scout bee phase offers a diversification mechanism that enables brand-new, probably impossible individuals to join the colony.

**2.4. Scout Bees phase of ABC algorithm:**

If the position of a food source is not updated for a preset period of cycles, it is presumed that the food source has been abandoned, and the scout bees phase begins. During this phase, the abandoned food source bee transforms into a scout bee, and the abandoned food source is replaced with a randomly picked food source within the search space. Therefore, the predetermined number of cycles, known as the limit for abandonment in ABC, is a critical control parameter. Assuming that the abandoned food source is $y\_{j}$, the scout bee will replace it with fresh $y\_{j}$, as follows:

$y\_{j}^{i}=y\_{min}^{i}+rand(0,1)(y\_{max}^{i}$-$y\_{min}^{i})$ ,$ ∀\_{i}=1,2,….D$ -------(4)

Where$ y\_{min}^{i}$ and $y\_{max}^{i}$ are the boundaries of $y\_{j}$ in $i^{th}$ direction.

**Algorithm.4.Scout bees phase**

|  |
| --- |
| if **cyclemod SPP=0****then**if **max(**$failure\_{i})>limit$**Replace** $y\_{j}$ **with a new randomly produced solution**endifendif |

Overall, two new control parameters are added to the ABC algorithm to improve its ability to converge for certain optimisation tasks. MR (Modification rate) and SPP (Scout production period) are the corresponding parameters. Another adjustment is the substitution of a selection method for the dynamic methodology. The suggested method's performance of the ABC algorithm using a dynamic strategy reduces execution time, boosts throughput, and improves network performance. The suggested ABC scheme outperforms existing techniques [33] like Flying Adhoc Network-Glowworm Optimisation (FANET-GSO), Integrated Glowworm Swarm Optimisation (IGSO), Unequal Clustering and Routing-Glowworm Optimisation (UCRA-GSO), and Integrated Glowworm Swarm Optimisation technique of Ant Colony Optimisation (ACI-GSO), which are shown in the following section, in terms of time efficiency.

 **3. Results and Discussion:**

This section provides a detailed description of the implementation results and functionality of our recommended framework. In order to confirm that our proposed framework outperforms the already employed approaches in terms of network performance, it also contains a comparison research.

**3.1 System Specifications:**

The proposed framework has been implemented in the MATLAB platform with the system specifications are listed below.

 **Platform :** MATLAB

 **OS :** Windows 8

 **Processor :** Intel Core i5

 **RAM :** 8GB RAM

**3.2 Simulation Outputs and Performance Evaluation:**

The simulation results of the suggested framework and performance assessment measures are described in this section. With the aid of pertinent assessment measures including cost, throughput, reliability, execution time, and energy consumption, the performance of the suggested framework has been assessed.



**Fig.2.Iteration Vs Best cost**

A best-cost artificial bee colony algorithm utilising a dynamic technique to improve wireless network performance is shown in Figure 2. The proposed technique decreases as the number of iterations rises, with the best cost of $10^{-3}$,$10^{-6}$ and $10^{-10}$achieved at the 20th iteration, 60th iteration, and 100th iteration, respectively.



**Fig.3.Reliability**

While increasing the time (sec), the reliability value gets decreases. The value of reliability reduces from 1 to 0.05 when time increases from 0 to 3x104 sec. Hence,robustness and accuracy of ABC-based reliability analysis are verified are shown in fig.3.



**Fig.4.Throughput**

The throughput of a network is a crucial indicator of how well a protocol performs. It speaks of all the packets that were transmitted from the network to the BS. Where the cluster head (CH) combines information detected by itself with information the cluster member nodes transmit to it and delivers the combined packet to the base station (BS). The dynamic approach used by the protocol results in a significant increase in network throughput even when the number of nodes is increased, as seen in Fig. 4.



**Fig.5.Throughput comparison**

In comparison to existing techniques [33] such as Flying Adhoc network-Glowworm optimization (FANET-GSO), Integrated Glowworm Swarm Optimization (IGSO), Unequal clustering and routing- Glowworm optimization (UCRA-GSO), and Integrated Glowworm Swarm Optimization technique of Ant Colony Optimization(ACI-GSO), Fig. 5 presents a throughput of the artificial bee colony algorithm with dynamic technique to give improved network performance in wireless communication. At different times (sec), the proposed technique accomplishes 260(kbps), which is 50kbps lower than FANET-GSO, which is 20kbps lower than ACI-GSO, which is 10kbps lower than IGSO are shown in fig.5.

**4. Conclusion:**

The artificial bee colony method was developed to address problems with data optimisation, and its performance was evaluated against that of cutting-edge algorithms. The unique methodology works well in compared to existing approaches. a situation where performance becomes better as the number of nodes rises. When a connection breaks, other protocols need to start the route discovery process afresh. With this capability, the ABC algorithm with dynamic method would be able to scale up to bigger networks and repair itself around the problem region. For smaller networks, it has a higher overhead, nevertheless. The testing results show that the recommended framework performs better than the competition in terms of high dependability, best cost, and enhanced throughput of 260 kbps, respectively.

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