**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**

With minimal battery power, wireless sensor networks (WSNs) may self-organize a sizable number of tiny sensor nodes [1]. With minimal battery power, wireless sensor networks (WSNs) may self-organize a sizable number of tiny sensor nodes. The network's sensor nodes are sufficient for aiding packet transfer despite the limitations of radio range. These sensor nodes can also locate, watch over, and identify actual things in real-time circumstances [2]. In order to deliver trustworthy data distribution, this sensor network comprises of an endless number of sensor nodes that may link to one another as well as an external base station [3]. Wireless sensor nodes can have a variety of desired characteristics, including low cost, compact size, high computing power, and ease of communication over short distances, and different functionality for data processing, routing, and sensing [4]. It is utilised for sensing and data aggregation tasks. For sensor devices in particular, it may be challenging to recharge them under bad circumstances when they are disregarded. To extend the network's life cheaply and effectively, the urgent problem of energy conservation of sensor nodes in a hostile environment must be solved [5]. To aid sensor nodes in conserving energy so that the focus may be on prolonging the network lifetime, a number of study methodologies have been published in the literature [6]. However, the performance of the network is negatively impacted by the sensor nodes' limited energy, memory, computing time, and computational capabilities. The network's longevity also depends on its ability to employ clustering effectively and the quantity of resources available. Three parts make up a practical clustering routing protocol: cluster setup, cluster heads (CHs) election, and data transfer. This is a practical way to lower WSN energy use. During the cluster setup phase, the sensor node groups in the detection zone organise into clusters of various sizes. The remaining nodes act as member nodes while certain nodes are elected as CHs during the CHs election phase using a specific electoral mechanism. During the data transmission phase, the member nodes are in charge of collecting environmental data and transferring it to the CHS. After data collection and processing, the CHs send the data to base stations (BS) of various sizes.

Clustering—the grouping of nearby sensor nodes into clusters—is essential for effective and efficient cluster management in this scenario. Each cluster has a designated sensor node called the cluster head (CH), which acts as an anchor in establishing connections between various cluster members as well as between cluster members and the base station. To put it another way, clustering is a strategy for grouping in which the cluster head nodes are entirely in charge of delivering the aggregated data from the sensor nodes to the base station [7]. This clustering method will likely be used at the highest level of network architecture to provide sensor nodes new tasks. The clustering method used by WSN increases the possibility of efficiency improvement and energy consumption optimisation.

Due to its incorporation with sensor technology, distributed information processing, embedded technology, wireless communication, and microelectronic approach, among other things, wireless sensor networks (WSNs) have developed into active study areas. Due to WSNs' advantages in low energy consumption and scattered self-organization, target tracking, environmental monitoring, national security, and underwater detection are just a few of the sectors that frequently use them. Due to its relationship to connectivity, energy efficiency, and network reconfiguration, coverage is a crucial WSN problem. It primarily focuses on how to configure the sensors such that there is appropriate service area coverage and that each point in the service area is maintained under observation by at least one sensor. There must be sufficient coverage for WSN to function properly. By installing sensors correctly, the network's configuration and communication requirements will be minimised, and resource management will be enhanced. The topic of path planning is crucial in the world of robotics. It is a technique for designing a path that prevents collisions when there are obstacles in the way. The path should be optimised using a realistic method that uses time, distance, or energy as the optimisation criterion, depending on the circumstances. where path planning may be done in both a known environment and an unfamiliar one. Finding your way around might be difficult because there isn't a map of the area that has been recorded [8]. Robots are equipped with sensors and a GPS, but because the world is unpredictable, they are unable to make precise plans in advance. Both traditional and intelligent path planning solutions exist [9].For robot route planning, the artificial bee colony technique was presented [10]. The primary objective of the suggested approach was to reduce the distance and travel time. [11] suggested using an artificial bee colony to design mobile robot paths effectively. Without clashing, the path is first built from the starting point to the final destination, and then it is optimised using the bee colony approach. This was achieved using the first plan. [12] presented a method for global convergence based on a chaos-hybridized artificial bee colony. In this study, a routing method based on the Artificial Bee Colony (ABC) algorithm—whose early performance results were presented in [13]—is examined using the round-based network lifetime. In a manner similar to this, the ABC algorithm is improved by including a probabilistic selection scheme that, in lieu of the basic ABC algorithm selection [14], assigns probability values to workable solutions based on their fitness values and to unworkable persons based on their violations. Honey Bee Optimisation (HBO), which performs better in terms of energy efficiency factors including scalability and network quality [16], was used to address this issue. HBO searches for the most cost-effective strategy to cut energy usage.In contrast, an effective optimisation methodology called the Lion (FLION) clustering algorithm was developed for energy-efficient routing. Therefore, the strength and longevity of network nodes may be improved by using this clustering technique that leverages a rapid collection of CHs[17]. As a consequence, the ABC technique's biologically inspired searching characteristics are used to construct the energy clusters.This test also takes the model's complexity into account. The suggested routing method for time-based WSNs that regularly deliver data is constructed using the ABC algorithm. The following is the paper's contribution:

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 ABC Algorithm is based on the foraging behaviour of honey bees. The swarm of honey bees is one sort of swarm that may be seen in nature. This insect colony uses its collective intelligence to find nourishment. The honey bee swarm exhibits a variety of traits, including the capacity to communicate, recall its surroundings, retain and spread information, and base choices on it. As a result, the Artificial Bee Colony algorithm has a small search area and is very sensitive to how the initial population is built. This is one of the key causes for the search space to shift to a more appropriate area as the population of potential solutions grows. The longevity of WSN is its most significant feature. Hubs are frequently joined together in groups headed by a pioneer, also known as a bunch leader, in order to maintain flexibility. 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.

**first source of food**

**Determine the nectar**

**Find the employed bee's new food position.**

**Determine the nectar**

**All onlookers distributed?**

**Keep in mind where the finest food supply is located.**

**Locate the leftover food**

**Create a new location for the drained food.**

**All onlookers distributed?**

**Final food position**

**Identify the nearby source of food for the spectator.**

**Choose a source of food for the observer.**

**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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