**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 ABC Algorithm is driven by the honey bee foraging behaviour. The honey bee swarm is an example of a swarm that may be seen in nature. This group of insects uses its collective intelligence to find nourishment. The capacity to communicate information, memorise the surroundings, store and distribute information, and base choices on that knowledge are just a few of the traits that the honey bee swarm possesses. As a result, the Artificial Bee Colony algorithm's sensitivity to the initial population construction is rather high, and its search space is constrained. One of the primary causes of the population of prospective solutions moving the search space to a better-fitting portion is due to this. The lifespan of the network is the most crucial factor in WSN. Therefore, hubs are typically assembled in groups headed by a pioneer, also known as a bunch leader, in order to maintain adaptability.In order to address the aforementioned problems, a unique ABC algorithm with a dynamic method has been presented in this work for data transmission to the base station and assistance to the overall hubs in transferring discovered data to target hubs. Hence, the use of energy by cluster head (CH) is more prominent than that of general hubs with improved network performance which is illustrated in fig.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 condition of artificial bees in the ABC algorithm is made up of scout bees looking for food sources at random, onlooker bees watching the movement of employee bees inside the hive to choose a food source, and employee bees associated with explicit food sources. Scouts and observers are sometimes referred to as "jobless bees." Honey bee scouts first find all food sources. From that point on, exploited honey bees and spectator bees start mistreating food supplies like nectar, which causes them to finally become depleted. The worker bee that was exploiting the depleted food supply at that point changes into a scout bee searching for new food sources. As a result, the worker bee whose food supply has run out becomes the scout honey bee. According to ABC, a food source's situation refers to the connected arrangement's quality, and a food source nectar measure refers to the associated arrangement's quality (wellness). The number of employed honey bees is equal to the number of food sources (arrangements), as each worker bee is completely linked to one and only one food source. The dynamic approach uses both the employee and spectator stages for data seeking. The following subsections provide descriptions of the suggested methods.

**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.

The ABC algorithm does not regard the initial population to be viable because initialization with feasible solutions is a time-consuming procedure, and in some circumstances it is impossible to construct a feasible solution randomly. For the parameters of solutions, random values between the lower and upper boundaries of the parameters are assigned during the initialization steps are shown in Algorithm 1.

**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). The step length steadily grows shorter as the search gets closer to the best result in the search space. As a result, the ABC algorithm makes a decision by developing a new food source. As a result, the ABC approach was modified to solve specific optimisation problems using a dynamic strategy, in which the algorithm's structure directs the answers to a workable area in the process as it runs. After all the employed bees have completed the search procedure, they calculate probability values and share the nectar information of the food sources, as well as their position information with the onlooker bees on the dance area, which are described in the below Algorithm.

**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, the ABC algorithm adds two new control parameters to increase its convergence capabilities for limited optimization problems. These are the MR (Modification rate) and SPP(Scout production period) parameters, respectively. Another change is to replace the dynamic technique with a selection method. The performance of the proposed method ABC algorithm with dynamic technique decreases execution time,increases the throughput,and increases the network performance. In terms of time efficiency, the results reveal that the suggested ABC scheme outperforms the existing technique [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) which are shown in below section.

**3. Results and Discussion:**

This part gives a thorough explanation of the implementation outcomes and the performance of our suggested framework. It also includes a comparative study to make sure that our suggested framework performs better than the already used methodologies in terms of network performance.

**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:**

In this section, the simulation outputs of the proposed framework as well as the performance evaluation metrics are presented. The performance of the proposed framework has been evaluated with the related evaluation metrics such as Cost, Throughput, Reliability, Execution time, and energy consumption.



**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**

A network's throughput is an important statistic for measuring protocol performance. It refers to the total number of packets sent from the network to the BS. Where, the cluster member nodes send packets containing information perceived by themselves to the cluster head (CH), which the CH combines with information sensed by itself and sends to the BS in packet form. The protocol achieves a good improvement in network throughput due to the dynamic technique, while increasing the number of nodes are shown 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 algorithm was introduced for data optimization issues, and its performance was compared to that of state-of-the-art algorithms. In comparison to other methods, the novel technique is effective. Where the performance improves as the number of nodes increases. Other protocols must re-initiate route discovery when a link fails. With this functionality, the ABC algorithm with dynamic technique would be able to repair itself around the failure area and scale up to larger networks. However, it has a greater overhead for smaller networks. The experimental findings reveal that the suggested framework outperforms the others in terms of the high reliability, best cost, and 260 kbps of increased throughput respectively.

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