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

Dr. Mirza Samiulla Beg, Assistant Professor, Department of Computer Science & IT, AKS University, Satna, mirzasamibeg@gamil.com

**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 little battery power, WSNs (Wireless Sensor Networks) can self-organize a huge number of tiny sensor nodes [1]. The network's sensor nodes are effective enough at aiding packet transfer despite the limitations of radio range. These sensor nodes can also detect, keep track of, and identify physical components in real-time situations [2]. In order to offer reliable data dissemination, this sensor network is made up of an endless number of sensor nodes that can communicate both with one another and with an external base station [3]. Wireless sensor nodes may have a variety of desirable characteristics, including low cost, compact size, high compute power, ease of communication over short distances, and several functional capabilities for data processing, routing, and sensing [4]. It is utilised for sensing and data aggregation tasks. In adverse circumstances where they are disregarded, sensor gadgets in particular pose a difficulty for recharging their power sources. In order to extend the network's lifespan cost-effectively and effectively, it is necessary to address the hot problem of energy conservation of sensor nodes in a hostile environment [5]. To preserve energy in sensor nodes so that the emphasis may be placed on prolonging the network lifetime, a number of research methodologies have been put out in the literature [6]. However, the limited energy, memory, computation time, and computational capabilities of the sensor nodes raise serious issues that impair the performance of the network. Additionally, the network's longevity is totally dependent on the quantity of resources available and the network's ability to employ clustering effectively. As a practical way to cut WSN energy consumption, a feasible clustering routing protocol is divided into three phases: cluster setup phase, cluster heads (CHs) election phase, and data transmission phase. During the cluster setup phase, the sensor node groups in the detection zone organise into clusters of varying sizes. In the CHs election phase, depending on a particular electoral procedure, certain nodes are chosen as CHs while the remainder nodes function as member nodes. Finally, during the data transmission phase, the member nodes are in charge of collecting environmental data and sending it to the CHS. After data collection and processing, the CHs transfer the data to base stations (BS) of various sizes.

In this context, clustering—the organisation of nearby sensor nodes into groups known as clusters—is important for achieving effective and efficient cluster management. 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 grouping method where the cluster head nodes are entirely in charge of sending the sensor nodes' aggregated data 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.

Due to its integration with sensor technology, distributed information processing, embedded technology, wireless communication, and microelectronic approach, among other things, wireless sensor networks (WSNs) have emerged as active study areas. Because of its advantages in low energy consumption and scattered self-organization ability, WSNs are frequently used in sectors such target tracking, environmental monitoring, national security, and underwater detection. Given its relationship to connectivity, energy efficiency, and network reconfiguration, coverage is a crucial WSN concern. It primarily concentrates on how to deploy the sensors such that there is enough coverage of the service area and that each point in the service area is monitored by at least one sensor. WSN has to have sufficient coverage in order to function well. If sensors are installed effectively, the network's configuration and communication requirements will be decreased, and resource management will be enhanced. The topic of path planning is crucial in the world of robotics. It is a technique for determining a route that avoids collisions when there are obstacles in the way. The path should be optimised using a workable method using time, distance, or energy as the optimisation criterion, depending on the circumstances. Where either a familiar or new environment may be used for path planning. Finding a route in an unknown area is a difficult task since the map of the environment is unknown [8]. Robots are fitted with sensors and a GPS, yet despite this, planning precisely in advance is impractical due to unpredictability. Path planning strategies come in two flavours: conventional and intelligent [9].For planning robot paths, the artificial bee colony method was presented [10]. The reduction of journey time and distance was the main objective of the suggested method. The artificial bee colony approach was introduced by [11] for effective path planning of mobile robots. A collision-free path from the starting point to the destination is first created, and then the path is optimised using the bee colony approach. The unique approach was employed to achieve this. [12] proposed a global convergence method 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. Similar to this, the ABC algorithm is expanded by incorporating a probabilistic selection scheme that awards probability values to viable solutions based on their fitness values and infeasible persons based on their violations [15], replacing the simple ABC algorithm selection [14]. Honey Bee Optimisation (HBO), which performs better in terms of energy efficiency measures including scalability and link quality [16], was presented as a solution to this problem. HBO searches for the most efficient technique at the lowest cost in order to minimise energy usage.Where, an effective optimisation approach called the Lion (FLION) clustering algorithm was developed for energy-efficient routing. Consequently, this clustering technique employing a rapid collection of CHs may be used to develop the energy and longevity of network nodes[17]. As a consequence, the ABC approach's biologically inspired searching characteristics are used to construct the energy clusters.With this test, the model's complexity is also looked into. The suggested routing method for time-based WSNs that deliver data on a regular basis is constructed using the ABC algorithm.

The contribution of this paper is as follows,

* To implement ABC(Artificial Bee Colony) algorithm using the dynamic technique.
* To pick a food source, follow the general scheme of the ABC algorithm (i.e., employee bees, onlooker bees, and Scout bees phase).
* Remember the finest solution attained so far.
* For searching data, implement the employee and onlooker phase in the dynamic technique.

The reminder of the paper has been organized as follows: section 2 presents the recent literatures; section 3 depicts the detail description of the proposed methodology; section 4 discusses the implementation results; finally, section 5 concludes the paper.

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

Honey bee foraging behavior is the motivation for ABC Algorithm. One of the swarms found in nature is the honey bee swarm, which searches for food in a collective cognitive manner. The honey bee swarm has several characteristics, including the ability to convey information, memorize the environment, retain and share information, and make decisions based on that information. Consequently,the initial population construction is relatively sensitive to the Artificial Bee Colony algorithm, and it has a limited search range. This is one of the main reasons for the population of potential solutions to migrate the search space to a better-fitting part.The network's lifetime is the most important issue in WSN. As a result, in order to sustain versatility, hubs are frequently gathered in groups led by a pioneer, commonly referred to as a bunch head.Thus to cope up with the aforementioned issues, a novel **ABC algorithm with dynamic technique** has been proposed in this work for transmitting data to the base station and assisting the overall hubs in sending detected 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.**

A novel ABC algorithm using dynamic Technique was created which has **Employee bees** associated with explicit food sources, **onlooker bees** watching the movement of employee bees inside the hive to pick a food source, and **scout bees** looking for food sources randomly make up the condition of artificial bees in the ABC algorithm. Both onlookers and scouts are also known as "jobless bees." Initially, scout honey bees locate all food sources. Where, utilized honey bees and onlooker bees begin to abuse the nectar of food sources from that point forward, and this repeated abuse will eventually deplete them. At that time, the employee bee who was exploiting the exhausted food supply transforms into a scout bee on the lookout for new food sources. As a result, the scout honey bee transforms into an employee bee whose food supply has been depleted. In ABC, a food source's situation refers to the quality of the linked arrangement, and a food source nectar measure relates to the quality (wellness) of the related arrangement. Because each employee bee is solely associated with one and only one food source, the number of used honey bees is equal to the number of food sources (arrangements).For data searching, the dynamic technique employs the employee and onlooker phases. The proposed approaches are described in the subsequent 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.

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 |

Based on the local information, and employee bee modifies (3) to the position of the food source (solution) in her memory and evaluates the nectar amount (fitness value, quality) of the new source (new solution). As can be observed from Eq. (3), the perturbation on the position $y\_{ji}$ diminishes as the difference between the parameters of the $y\_{ji}$and $y\_{ki}$decreases. As the search gets closer to the best solution in the search space, the step length gradually decreases. Therefore,the ABC algorithm chooses by creating a new food source. Consequently, the modification of the ABC method to address limited optimization issues using a dynamic technique, where the structure of the algorithm steers the solutions to a feasible region in the running process. 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=**$\frac{S\_{n}}{2}$ |

Following the distribution of all onlookers, food sources that are no longer worth exploiting are determined. If a solution cannot be improved after a certain number of cycles ("limit"), it is abandoned. The scouts discover a new food source to replace the one that the bees abandoned. This is done by creating a random position and then replacing it with the abandoned one.Hence,the algorithm scout bee phase provides a diversity mechanism that allows new and likely infeasible individuals to enter the population are shown in Algorithm 4.

**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 section provides a detailed description of the implementation results as well as the performance of our proposed framework, also the comparison analysis to ensure that our proposed framework outperforms the existing techniques in 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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