An Artificial Bee Colony algorithm for Efficient Optimized Data Aggregation to Agricultural IoT Devices Application

C. Sathish[1*] and K. Srinivasan[2]

[1] *Department of Computer Science, Periyar University, India*
[2] *Department of Computer Science, Periyar University Constituent College of Arts and Science, India*
[*] *Corresponding author. E-mail: Sathish321e@gmail.com*

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The current world have structured and gained numerous advantages from state-of-the-art of digital and computerized technologies. Internet of Things (IoT) has recently started playing a key role in day-to-day lives, stretching perceptions, and having the capability to monitor our surrounding environment. The definition for agriculture is given as the practice, science, or art for soil cultivation, crop production utilizing diverse techniques of preparation and technologies, and marketing of farming's end products. Farmer efficacy and effectively can be enhanced with Wireless Sensor Network (WSN) installation for agricultural practice optimization. Gathering of data from multiple sensors is done during data aggregation. To optimize the data aggregation, metaheuristic methods are applied. The processes of mutation, crossover, and natural selection, are replicated in the evolutionary algorithm known as Genetic Algorithm (GA). Artificial Bee Colony (ABC) algorithm's primary benefit is that it does not get trapped in the calculation of their local minima, and that it also considers the global and local search. An Artificial Bee Colony (ABC) algorithm has been proposed.

Keywords: Genetic Algorithm (GA), Artificial Bee Colony (ABC), Wireless Sensor Network (WSN), Data aggregation devices, Internet of Things (IoT)

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1. Introduction

Mobile and Cloud computing, Big Data, Internet of Things (IoT) are few of the latest technologies which have been lately devised. These days, the world is gradually moving in the direction of smart world concepts like smartphones, smart homes, smart cities, and so on. For the global movement of agriculture towards a more sustainable and productive path, the utilization of IoT [1] and sensors is quite vital. The latest advancements in Information and Communication Technology (ICT), WSN, and IoT have the potentiality to address this sector's certain technical, economic, and environmental hindrances and also opportunities. With the continuous growth of interconnected devices, this has led to the generation of more Big Data with multiple modalities, temporal variations, and spatial variations. This Big Data's intelligent processing and analysis are essential for development of a higher knowledge base level and insights, which leads to reliable sensor management, better decision making, and forecasting.

In the Indian economy, agriculture has a significant role, and it is also the way of life for many Indians [2]. The introduction of the concept of Smart Agriculture is to deal with the large loss to farmers due to crops destroyed by inappropriate maintenance. State-of-the-art technologies are utilized for crop production enhancement with precision agriculture. It aids in system monitoring, and it also provides information related to diverse aspects of the environment. An extensive agricultural parameter range is tracked in smart farming for crop yield enhancement, for cost reduction, and optimization of process inputs, like greenhouse production environment, weed management, fertilizers and pest, irrigation water, soil status, growth status, and conditions about the environment. As an approach to green technology, smart farming attempts to minimize traditional farming's ecological footprint. Smart irrigation and minimized pesticide and fertilizer usage on crops in precision agriculture, can greatly decrease emissions and leaching issues, and also the climate change impact.

Internet of Things (IoT) is an emerging technology and is now being used in various applications. In IoT devices, machines, laptops, mobile phones, equipments are connected through Internet with a capacity of intelligent behaviour [3]. The main requirements of the IoT are: an understanding of the requirements of the user and their application; communication network required for connecting all the devices and software tools to intelligently use the data acquired. The main concept of IoT is context-aware applications between anything, anywhere and anytime. It is applied in various domains and common applications are health monitoring, smart city, traffic control, agricultural applications and so on. It relies on RFID and sensor network technologies in the implementations.

In modern wireless communication, very revolutionary technology is the IoT. IoT's fundamental concept is the interaction between numerous objects or physical things utilizing specific addressing schemes to being Internet-connected. Many vertical markets like agriculture, smart home, vehicles, healthcare, transportation, and industry, utilize applications related to IoT technology. In agriculture, for the enhancement of cultivation practices, IoT devices give valuable information about an extensive physical parameter range. WSN's role in IoT technology is of critical significance due to the wireless data transmission dependency of large majority of IoT applications in numerous markets. Data aggregation is helpful in conserving the energy in a wireless network. During data aggregation, redundant data is removed, reducing the volume of the data transmitted leading to lesser power consumption. The only drawback of data aggregation is the data latency occurring due to the wait time of each node for receiving data from other nodes [4]. By diminishing the quantity and size of data transmission, data aggregation [5] also tries to increase the network's lifespan. There are two ways to perform data aggregation. One way is to integrate the incoming packets from many sources without processing them and sending packets. Another way is to reduce the transmission of data to the source and compression of data. Recent developments in computational intelligence have made these systems enter WSNs. For observing the network performance, evaluation of the following environmental parameters is needed: signal strength, hop count, power consumption, power capacity, bandwidth, energy efficiency, delay, data accuracy, and network lifespan.

Due to its capability of global search [6], optimal features are efficiently chosen by the swarm intelligence-based methods. The proposed technique's feature selection is treated as a global optimization problem. Applications that have large search space and do not place much priority [7] on the precision of the results, GA is often utilized. Being comparatively computation-intensive, the execution of GA occurs only at the Base Station. This algorithm is utilized to produce energy-efficient and balanced data aggregation spanning trees for WSNs. A chromosome will indicate a data aggregation tree in which the node is determined by the gene index, and the parent node is determined by the value of the gene. Standard genetic operations like elitism, tournament selection, mutation, and single-point crossover, are utilized for getting the next generation. Moreover, the number of generations and the size of the population depend on the node numbers.

Particle Swarm Optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution about a given measure of quality. ABC is based on PSO. In comparison to various other biological metaheuristic algorithms, ABC has multiple benefits. ABC has minimum control parameters and a very simplistic structure. ABC's various benefits have caught the attention of numerous researchers, and this proposed method utilizes feature selection that is on the basis of the ABC algorithm. If there is an extraction of a high number of features, then there will also be an increase in the complexity. The system efficacy and accuracy may be diminished by the high number of features. ABC algorithm's key goal is the optimization of mathematical problems. Various real-time problems can be resolved by use of the honey bees' intelligence behaviour. ABC algorithm's performance is suitable for applications related to engineering by taking into consideration both minima, that is, global and local.

This work has proposed the Artificial Bee Colony (ABC) algorithm and the Genetic Algorithm (GA) for IoT device optimization and its agricultural application. Reviews of literary works are presented in Section 2. Several processes utilized in this work are detailed in Section 3. Experimental results are explained in Section 4, and the work is concluded in Section 5.

2. Theory and formula

A WSN-based system for the optimal watering of agricultural crops was devised by Muangprathub et al. [8]. The goal of this work was to devise and construct a control system utilizing node sensors in the crop field with data management through a web application and smart phone. Hardware, web application, and mobile application are the three components of this system. Design and implementation of the first component was done in control box hardware that is connected for gathering data about the crops. The field is monitored by use of soil moisture sensors which are connected to the control box. Second component is a web-based application which was devised and deployed for the manipulation of details of field information and crop data. Data mining is utilized in this component for the analysis of data for prediction of feasible soil moisture, humidity, and temperature for crop growth's optimal future management. Third and final component is a mobile application in a smart phone which is majorly utilized for controlling the watering of crops. Crop watering can be manually controlled by the user or automatically done. Data from soil moisture sensors can be utilized for watering in automatic control. In functional control mode, crop water can be manually controlled by the user. For the LINE application, notifications are sent by the system through LINE API. The implementation and testing of this system was done in Thailand's Makhamtia District in Suratthani Province. In agriculture, outcomes have proved that this implementation is quite beneficial. Soil's moisture content could be properly maintained for agricultural productivity maximization, cost reduction, and growth of vegetables. Pushing agriculture in path towards digital innovation is represented in this work.

As an application to smart agriculture made up of diverse levels of design, Haseeb et al. [9] proposed a WSN framework that was based on IoT. Initially, the relevant data is caught by the agricultural sensors, and depending on a multi-criteria decision function, a cluster head set is determined. Signal strength on the transmission links is also assessed whilst utilizing signal to noise ratio (SNR) for accomplishing data transmissions that are effective and consistent. Secondarily, there is provision of security for transmission of data from the agricultural sensors towards Base Stations (BS) whilst employing linear congruential generator's recurrence. Outcomes of the simulations verified that, in comparison to other solutions, the communication performance for smart agriculture was greatly boosted by the proposed framework as an average of 26% in routing overheads, 16% in energy consumption, 13.5% in network latency, 38.5% in packet drop ratio, and 13.5% in network throughput.

A survey of the latest research on UAV and IoT technology employed in agriculture was done by Boursianis et al. [10]. There was description of the IoT technology's fundamental principles such as IoT solutions and applications in smart farming, protocols and networks utilized in agriculture, types of IoT sensors, and intelligent sensors. UAV technology's role in smart agriculture was also represented through the analysis of UAV applications in several scenarios like field-level phenotyping, management of crop diseases, monitoring of plant growth, management of weeds, pesticide usage, fertilization, and irrigation. Additionally, analysis was also done on UAV system usage in agricultural environments that are complicated. This survey has concluded that UAV and IoT are two extremely significant technologies capable of transforming traditional practices of cultivation into precision agriculture's latest intelligence perspective. An IoT device is utilized in Rajeswari et al. [2] for sensing the agricultural data and storing it in a Cloud database. Big Data analysis that is based on Cloud is utilized for studying data, that is, crop's stock and market requisites, crop analysis, and fertilizer requisites. Later, prediction is done depending on the method of data mining which information gets to the farmer through the mobile application. The intention of the proposed work is to boost the production of crop and control the agricultural product cost through this predicted information's utilization.

For WSNs, Islam et al. [7] employed a Genetic Algorithm (GA) for the generation of energy efficient and balanced data aggregation spanning trees. A single best tree will use the least energy from every nodes, yet, allocates more load to certain sensors in the data gathering round. So, there will be early depletion of the heavily loaded nodes' energy resources compared to other nodes. Hence, a tree collection can be utilized to use up lower energy and also balance the nodal loads. These two issues in the generation of aggregation trees are dealt with by this proposed GA. An open source simulator, 1-sim, is employed for this GA's simulation. Simulated outcomes demonstrate that proposed GA surpasses the performance of other data aggregation tree-based approaches with regards to network lifespan prolongation.

An effective and novel metaheuristic in a Genetic Algorithm form was proposed by Hanh et al. [11] to overcome the existing metaheuristics' numerous weak areas and also to determine an exact method for this problem's fitness function evaluation. Constituents of the proposed genetic algorithm were a procedure for heuristic population initialization; the fitness function's proposed exact integral area calculation, and a Laplace Crossover and Arithmetic Crossover Method operator combination. Over an extensive problem range, this proposed algorithm has been experimented on to be compared against five other advanced methods. In majority of the tested instances, results demonstrate this algorithm's delivery of superior performance with regards to stability and quality of solution.

An IoT Network that was made up of Base Stations and Wireless Sensors was studied by Zhang et al. [12]. There is an increase in the development of wireless power transfer methods for providing battery charging. It is the responsibility of the charging vehicle to supply electrical power in wireless sensors [13]. The discussed IoT network scenario's transfer of data has been expressed as a problem of minimization in order to conserve electrical energy. The optimization problem can be dealt with by proposing a three-stage method. The data transfer model's sub problems can be resolved by proposing a restart artificial bee colony (RABC) method. This method has been verified to converge asymptotically towards the problem's optimal solution. Mathematical experiments demonstrate that this studied network scenario's energy usage can be decreased through utilization of the proposed method with a property that is robust and good.

An advanced method of feature selection, Artificial Bee Colony (ABC) algorithm, was assessed by Taghizadeh-Mehrjardi et al. [14] for reduction of the number of auxiliary variables which are derived from remotely sensed data (for example, Landsat images) and a digital elevation model (DEM). For three-dimensional mapping of soil organic matter (SOM) in the Big Sioux River watershed at South Dakota in United States of America, there is application of a combination of data miner methods (Artificial Neural Network (ANN) and Support Vector Regression (SVR)) and depth functions (for example, spline, logarithmic, and power). At the soil surface, the ABC feature selection algorithm showed that remote sensing data (for example, NDVI) are powerful predictors. But, as the soil depth increases, the relevancy of terrain parameters (for example, wetness index) becomes stronger. Mean R2 values that was evaluated by 10-fold cross validation showed that SVR model could describe about 50% of the total SOM variability whilst the ANN model could describe about 57% of the total SOM variability. But, upon application of the ABC algorithm, there was increase in the predictive power of both models, especially when it was merged with the ANN model. Experimental results demonstrated that, for explanation of the SOM's 3D spatial distribution across the study watershed, DSM approaches are powerful and significant tools.

3. Technology interventions

3.1. Genetic Algorithm (GA)

As a stochastic optimization technique, Genetic Algorithm (GA) is dependent on metaheuristic search processes. A matrix of population of solution indicates the start of a GA. This matrix's rows depict randomly generated individuals. Every individual depicts an objective function's solution. An individual in GA is defined as all solutions that are gene encoded. Through use of an objective function, there can be evaluation of the fitness of individuals as per the objective function. Improvement of population can be attained by combining genetic information from diverse population members. Crossover is the term fiven to this process. Mutation is yet another technique of improving the population by mutating certain individuals of the population as per the population's rate of mutation.

Resolution of the optimization problem is done by an evolutionary algorithm known as Genetic Algorithm (GA). GA's primary intention is to alter the initial solution through utilization of mutation, crossover, and local improvement for the optimal position's [14] identification. GA will randomly generate the initial and change it through mutation and crossover. Proposed algorithm's framework for placement of sensors is offered as below:

1. **Representation**: Representation of chromosomes are in the nXn matrix form, in which the number of sensors is denoted as n (Let us say, n = 8). For random sensor placement in the A region, whilst every chromosome's sensor position and entry begins from 0 to AxA.

2. **Initial Population**: For optimal sensor placement, there is random generation of more than 100 initial populations. There is random generation of the given sample population; the matrix comprises of 4 rows and 4 columns, that are based on sensor availability.

3. **Crossover**: This process refers to gene exchange between chromosomes. A value between 1 to n is randomly chosen by the GA.

4. **Mutation**: To get the optimal solution, certain genes in the chromosome are modified in this process.

3.2. Proposed Artificial Bee Colony (ABC)

Swarm intelligence is an upcoming field of study for various researchers. This is categorized as an evolutionary computing branch. The definition of swarm intelligence is given as the measure which introduces the collective behaviour of social insect colonies or other animal societies for the algorithm design or distributed problem solving devices. Evaluation of fitness is done by Nature-based and Population-based optimization algorithms. Thus, there is expectation for the population of possible solutions to move in the direction of the search space's better values of fitness.

ABC algorithm does a simulation of the bee swarm's behaviour of honey collection. It also categorizes the different bee behaviours as per their corresponding labour divisions, and also communicates the information and sharing of bee swarm for optimal solution accomplishment. Scouts, onlookers, and employed bees, are the artificial bee swarm's three divisions by the ABC algorithm. At every search process, the food source is successively mined by the guiding bee and its following bee, which is, the optimal solution search is done. The scout will check if it has been captured in the local optimum, and will also search randomly for other potential sources of food sources when it is caught in a local optimum. A potential solution to the problem is represented by every source. The solution's quality is associated with the amount of nectar from the source of food.

Differences between ABC algorithm and other SI algorithms occur in the bee roles which may be reversible. If there is no improvement of the food source information even after many iterations, there is halting of the food source information, and the bees turn into scouts. ABC's benefits are its rapid converging speed and its strong global search capability. ABC's drawbacks are its poor race diversity, when the solution nears the global.

In an ABC algorithm's instance, scouts, employed bees, and onlookers constitute the three diverse groups of every artificial bee colonies. In the instance of food source, in which an employed bee is just taken as a single bee. There are certain scouts termed colony explorers in each colony. Further characterization of the scouts is done through a search cost which was low in the instance of a food source's quality. Sometimes, accidental discovery of unknown food sources by the scouts do happen. ABC algorithm also has a food source position which may be a potential solution to optimization problems and the actual quantity of food source that is the nectar corresponding to this solution's fitness quality. These solutions will be equivalent to the number of onlooker or employed bees. Fig. 1 depicts the ABC algorithm's short pseudo-code.

In ABC algorithm, gathering of artificial bees is considered to be nodes where every node cluster is classified into three groups: scouts, onlooker bees, and employee bees. At the cluster's each node, a wait is conducted on the dancing area for best optimal path selection. Available food's position is equivalent to a certain possible solution for the optimization problem that depends on the fitness of the quality of the food choice. When a bee has found nectar or food, it signals other bees through dance stigmergy which will indicate the food's location and quantity, thus, attracting numerous bees towards the food. Trial number for release of stored food and the value of limit is the same since it is the ABC's [15] critical control factor. The summary of this emergent intelligence behaviour which is inherent in foraging bees is provided as follows:

1. Initialize the population of solutions
2. Evaluate the population
3. Produce new solutions for the employed bees
4. Apply the greedy selection process
5. Calculate the probability values
6. Produce the new solutions for the onlookers
7. Apply the greedy selection process
8. Determine the abandoned solution for the scout, and replace it with a new randomly produced solution
9. Memorize the best solution achieved so far

Fig. 1. Pseudo-code of the ABC algorithm.

1. Foraging process's first phase is the seeking of food source from the environment. The solutions will be represented by:

$$min\ f = f(x),\ x = (x_1, x_2, ...x_m \in S,\ S = [x_{iL}, x_{iH}] \quad (1)$$

In which, the m - dimensional variable is x, the objective function is f and the upper and the lower bounds of ith-dimensional variable are $[x_{iL}, x_{iH}]$. If N is the total number of employed and onlooker bees, then 2N locations are located randomly.

2. Second phase will be the starting of exploitation of the identified sources in order to be an employed forager. The nectar is gathered by this employed bee. It will then go back the hive to offload the honey, and dance stigmergy is utilized for information sharing with the rest of the bees. Upon depletion of the food source, the employed bee will turn into a scout that seeks another source of food. New sources of food explored by employed bees

$$V_{ij} = x_{ij} + R_{ij}(x_{ij} - x_{kj}) \quad (2)$$

In which the V_{ji} denotes a new location, R_{ji} will be a random number in the range [-1, 1], k = 1, 2, 3... N and the k $\neq$ i.

3. Third phase consists of the onlooker bee waiting in the hives, getting dance signal for a scout bee, and picking a site on the basis of the quality of food and the dance frequency. After each onlooker bee explores the source

of food in the neighborhood xi. The probability Pi has been calculated as in Eq. 3:

$$P_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i} \tag{3}$$

In an optimal path, each node has a position that denotes the best optimal solution and the amount of nectar which is utilized for the fitness quality's evaluation for the environment's optimal path, and is evaluated as per Eq. 4:

$$fit_i = \frac{1}{1 + fit_i} \tag{4}$$

Where, fit_i is the fitness value of i^{th} employed bee, f_i is the objective function value of i^{th} the employed bee.

Each node transmits data to the cluster's other nodes, in which there is estimation of value of fitness. The analysis of the function of fitness that is computed based on the weight function for a small set of parameters such as the node and its cluster, which gets a power level for all nodes, the battery level, and the trust factor. Trust a value evaluates will the previous work's extension, and is computed depending on the food source from the fitness function 4. Any artificial onlooker bee elects an optimal path that is fitness function 4 dependent.

4. Results and discussion

The GA and ABC methods are used. Experiments are carried out using 200 to 1000 numbers of nodes and 0 to 800 number of rounds. End to end day on network refers to the time taken for a packet to be transmitted across a network from source to destination device, by Eq. 5.

$$\text{End to delay} = \frac{\text{Total delay involved in sending \& reception of the packets}}{\text{Total number of received packets}} \tag{5}$$

Packet Delivery Ratio (PDR) is the ratio of the data packets delivered to the destinations to those generated by the sources at the application level. Lower value reflects a larger number of packets being dropped due to link failures or network congestion. Hence higher PDR proves the effectiveness of the routing protocol in successful delivery of packets, by Eq. 6.

$$\text{Packet Delivery Ratio} = \frac{\text{Total data packets received at destination node}}{\text{Total data packets generated at the source node}} \tag{6}$$

Network lifetime in terms of number of alive nodes with respect to the number of rounds. The alive nodes are those nodes that have their energies as non-zero. Table 1 shows the parameters of ABC. The average end to end delay, Average Packet Delivery Ratio (PDR) and lifetime computation as shown in Tables 2 to 4 and Fig. 2 to 4.

Table 1. Parameters of ABC.

Parameters	Values
Numbers of bees	200
Maximum number of cycles (MCN)	500
Number of iterations for onlooker bees	200
Number of food sources	25
Random scouts	1
Upper bound	10
Lower bound	-10

Table 2. Average End to End Delay for ABC.

Number of nodes	GA	ABC
200	0.0018	0.0019
400	0.0023	0.0019
600	0.0217	0.019
800	0.0261	0.03
1000	0.059	0.0678

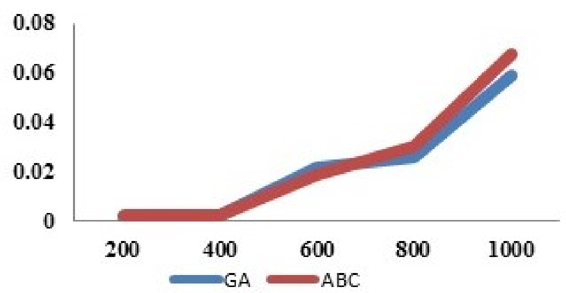

Fig. 2. Average End to End Delay for ABC.

Fig. 2 shows that the ABC has lower average end to end delay by 5.41% for 200 number of nodes, by 19% for 400 number of nodes, by 13.3% for 600 number of nodes, by 13.9% for 800 number of nodes and by 13.9% for 1000 number of nodes when compared with GA respectively.

Sample Percentage Calculation for average end to end delay (200 number of nodes):
%AGE=ABS (ABC - GA)/AVG (GA,ABC)
= 100 x ABS (0.0019 - 0.0018)/(0.0019 + 0.0018/2)
= 5.41%

Fig. 3 shows the ABC has higher average PDR by 8.6% for 200 number of nodes, by 10.9% for 400 number of nodes, by 24.53% for 600 number of nodes, by 17.9% for 800 number of nodes and by 13.44% for 1000 number of nodes when compared with GA respectively.

Table 3. Average Packet Delivery Ratio for ABC.

Number of nodes	GA	ABC
200	0.7481	0.8152
400	0.7267	0.8103
600	0.6743	0.8628
800	0.6392	0.7648
1000	0.6434	0.7361

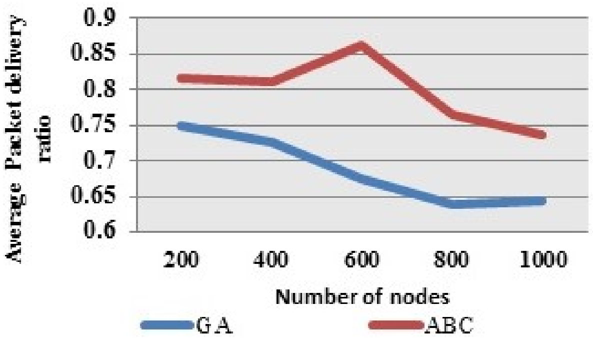

Fig. 3. Average Packet Delivery Ratio for ABC.

Sample Percentage Calculation for Average PDR (200 number of nodes):

%AGE=ABS (ABC - GA)/AVG (GA,ABC)

= 100 x ABS (0.8152 - 0.7481)/(0.8152 + 0.7481/2)

= 8.6%

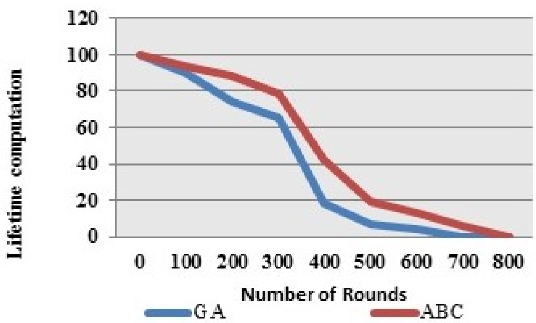

Fig. 4. Lifetime Computation for ABC.

Fig. 4 shows that the ABC has higher lifetime computation by 4.35% for 100 number of rounds, by 17.3% for 200 number of rounds, by 19.44% for 300 number of rounds, by 80% for 400 number of rounds, by 92.34% for 500 number of rounds and by 105.9% for 600 number of rounds when compared with GA respectively.

Sample Percentage Calculation for Lifetime Computation (100 number of rounds):

%AGE=ABS (ABC - GA)/AVG (GA,ABC)

= 100 x ABS (94 - 90)/(94 + 90/2)

Table 4. Average Packet Delivery Ratio for ABC.

Number of rounds	GA	ABC
0	100	100
100	90	94
200	74	88
300	65	79
400	18	42
500	7	19
600	4	13
700	0	6
800	0	0

Table 5. Network Lifetime Comparison of ABC with GA.

Rounds	Extra percentage of nodes alive for ABC compared to GA
100	4.35%
200	17.3%
300	19.44%
400	80%
500	92.34%
600	105.9%

= 4.35%

It is observed from Fig. 5 that till 300 rounds the percentage of nodes alive is higher for ABC in the range of 4.35% to 19.44% when compared to GA. As the rounds increase above 300, the ABC has a significantly higher number of nodes live when compared to GA due to the optimal data aggregation and energy efficiency achieved by ABC. As all the nodes die before the 800th round, the maximum number of rounds is shown as 800. At round 400, 18 nodes are alive for GA and 42 nodes for ABC. Thus, the proposed ABC performs better.

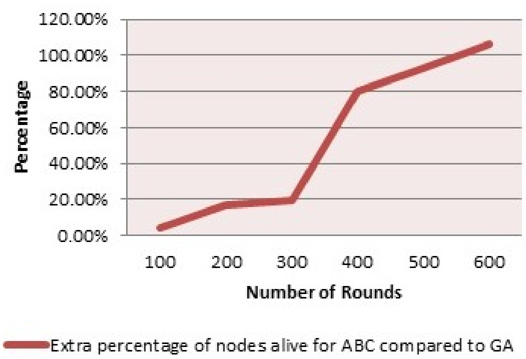

Fig. 5. Network Lifetime Comparison of ABC with GA.

5. Conclusion

In WSNs which are based on IoT, the most sought after topic of research is related to maximization of network longevity whilst optimal coverage accomplishment. IoT utilization results in Big Data or large-scale which offers information that is useful. Experimental results demonstrate that, for 200 number of nodes, the ABC has a higher average PDR by 8.6%, and a lower average end to end delay by 5.41% in comparison to the GA. For 400 number of nodes, the ABC has a higher average PDR by 10.9%, and a lower average end to end delay by 19% in comparison to the GA. For 600 number of nodes, the ABC has a higher average PDR by 24.53%, and a lower average end to end delay by 13.3% in comparison to the GA. For 800 number of nodes, the ABC has a higher average PDR by 17.9%, and a lower average end to end delay by 13.9% in comparison to the GA. For 1000 number of nodes, the ABC has a higher average PDR by 13.44%, and a lower average end to end delay by 13.9% in comparison to the GA.

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