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Comparative Analysis of Bio Inspired Optimization Techniques in Wireless Sensor Networks with GA-PSO Approach

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Abstract

Objectives: This research paper is fixated to evaluate the performance of wireless sensor network by employing Bio inspired optimization techniques. In this work, it has been proposed to explore the possibilities of optimization procedures in order to improve the performance of wireless sensor networks. **Methods/Analysis:** We seek to optimize the Quality of service in wireless sensor network via routing. In order to raise the lifetime of the wireless sensor network load balancing of cluster heads is implemented here in this research work with this the energy consumption could be reduced long with less Error Rate and less Routing Overhead, Minimization of End to end delay and improving Throughput. **Findings:** In this work, the performance analysis has been evaluated for the different optimization techniques like Genetic algorithm, Particle Swarm optimization, and bacterial foraging optimization and Hybrid approach of GA-PSO optimization. First of all, the optimization techniques such as GA, PSO and BFO are adopted separately on WSN setup and after that the hybridization of GA and PSO is employed. In the existing work Load balancing was employed with GA optimization but in this work other techniques are also taken along with hybridization of GA and PSO. A comparison on the performance analysis of all the optimization algorithms is specified and to infer which of the techniques performs better in order to maximizing the network lifetime and minimizing the end to end delay of the wireless sensor network so that packets transferring is carried efficiently with a reduced amount of error rate so that there will be a lesser chance of the node failure and extend the network lifetime for the awareness of routing optimization. **Improvement:** Further hybridization of other optimization techniques can be implemented for the improvements of wireless sensor networks.

Keywords: Wireless Sensor Networks, Network Performance in Terms of Network Lifetime and End to End Delay, BFO, GA, GA-PSO, PSO

1. Introduction

Wireless Sensor Network primarily comprises numerous wireless nodes that are mostly known as sensor nodes and more than one base station designated as the sink. On the basis of their sensing mechanism[1], these sensor nodes accumulate data from the surroundings. The nodes are placed arbitrarily in such a way that together they collaborate to compose an ad hoc network, which is proficient of communicating to the data collecting sink or the base station. There are several applications of the wireless sensor network such as health monitoring, target tracking, habitat monitoring and building monitoring. The prime liability of the sensor nodes in every application is to judge the destination and transfer their obtained data to the sink node for advance procedures. In large-scale data-collecting networks, the sensor nodes are usually run by small and economical batteries[2]. Every single sensor node creates its judgements individually on the basis of its assignment, the information it presently possesses,

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awareness of its computing, communication, and energy resources. Each node is required to have the proficiency to accumulate and direct the data via specific route either to other nodes or back to an outside base station or stations that may possibly be a static or a movable node proficient of linking the sensor network to the current communication set-up or directly to the internet[3].

The limitations of the resources and unpredictability of low-powered wireless links of the sensor nodes[4], in addition with a number of performance stresses of different applications enforce several obstacles in formulating an effective communication protocol for wireless sensor networks[5]. In the intervening time, framing an appropriate routing protocol in order to satisfy the performance requirements of several applications is reckoned as a significant matter in wireless sensor networking. The foremost constriction in proposing a routing protocol in WSNs is the inadequate power of the sensor nodes which commands the design of energy-proficient communication protocol. As per the comparison with the flat and multi hop communication cluster based structural design offers extended lifetime[6]. Since, the clustering technique is energy proficient when it is compared with the single and multi-hop routing this is the only reason because of which it is utilized for communication among nodes and sink. According to the clustering technique, one of the sensor nodes within the cluster will be designated as Cluster Head (CH), which is accountable for transmitting the data from each sensor to the remote receiver. In this technique, few CH nodes are profoundly loaded, and then energy reduction will take place. In order to acquire constant energy reduction, load balancing over clusters (i.e. same number of nodes to each cluster) is introduced[7,13,25].

Wireless sensor networks have recently attained the collective attention equally from the research community and authentic users. Several clustering algorithms regarding different contexts have already been proposed previously[7-9]. Among those algorithms many algorithms are particularly focus on reducing the energy consumed in the standardized system. Generally, routing turns out to be an extra challenging and evaluative, once the size of the network scales up. Recently, the biologically-inspired intellectual algorithms have been established in order to deal with this particular issue. The software agents can be formed to unravel complex issues, by employing ants, bees and other social swarms as models, such as traffic re-routing in busy telecommunication networks[24]. In[25] proposed a load balanced clustering algorithm on the basis of Genetic Algorithm for Wireless Sensor Network, which can perform much better similarly for both equal as well as unequal load of the sensor nodes and then the results are compared with further interrelated clustering algorithms and also with some of the evolutionary based approaches. In[10] delivers the guiding principles regarding the means of broadcast, clustering and battery-operated energy of ordinary and CH nodes.

In[11] investigated the heterogeneity along with a novel clustering algorithm that further helps to decide the cluster head on the basis of the node energy. CH selection algorithm was required as LEACH. In[12] described about flexible clustering and power control for the homogeneous sensor networks. In[13] presented a review on mechanisms for WSN on the basis of energy proficient scheduling. Subsequently, in PEGASIS, there is no centralized mechanism regarding cluster formation[14,15] therefore in order to accomplish hierarchical distribution of energy each node has to spend extra energy while performing data aggregation. In[16] considered a clustering algorithm CODA in order to release the disproportion of energy reduction triggered by different distances from the sink. Robust CODA segregates the number of clusters the basis of the distance to the base station. In case of single hop clustering, the cluster formation depends on the distance of the base station i.e. the longer the distance to the base station, the more clusters are formed. In HEED, author presents a variable that defines the transmission power to be used for intra-cluster broadcast. The proposed variable is frequently known as cluster radius[17]. HEED accomplishes reasonably even distribution of cluster heads over the network and abort within a persistent number of repetitions.

There are certain problems in WSNs that have been expressed as multidimensional optimization problems, and are resolved by utilizing bio-inspired methods. There are also some additional problems that are frequently expressed as optimization problems such as node placement, data collection, localization, and energy-based clustering[18,19]. As sensor networks scale up in size, the management regarding distribution of the networking load effectively will be the deepest concern of the sensor nodes. Load balancing averages the consumption of energy in an effective way by distributing the workload among the clusters in sensor network. Load balancing is also beneficial in order to minimize the congestion hot spots, which in-turn leads to the reduction of wireless collisions.

Thus, the way proposed here is to seek out the investigation regarding the difficulties of balancing the energy utilization and extending the lifetime of the network along with the reduction of delay for WSNs. Hybrid algorithms can be established on the basis of the bio inspired algorithms, which can be further employed in order to enhance the performance of wireless sensor networks. A very innovative approach has been proposed by merging the clustering method for load balanced and swarm intelligence for picking up the ideal routing path from the source to the destination by favouring the maximum residual battery power.

2. Bio-Inspired Optimization Techniques

For the enhancement of the research, optimization techniques, namely, Genetic algorithm, Particle Swarm Optimization and Bacterial Foraging Optimization has been utilized and the explanation for the same is defined below:

2.1 Genetic Algorithm (GA)

Genetic algorithms (GA's) are the search algorithms that work through the course of natural selection[20]. They initiate through a sample set of probable resolutions which further evolved as a collection of ideal explanations. The resolutions that are poor tend to perish within the sample set whereas, on the other hand, better resolutions mate and spread their beneficial qualities, which consequently leads to the introduction of more solutions within the set that boast better potential (for each new solution added, an old one is removed. Whereas, the overall set size remains persistent)[21]. A diminutive random transformation benefits that a set never deteriorate and unaffectedly gather abundant replicas of the exact solution. Generally, genetic algorithms possess the tendency to perform well than the previously proposed optimization algorithms since they are less expected to be directed off course by local optima.

Genetic Algorithm has been shown below in the form of an algorithm:

Initialize population;
Estimate population;
While Termination Criteria Not Satisfied
Select parents for reproduction;
Perform crossover mutation;
Repair (); Estimate population ;}}

2.2 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is primarily defined as a mutative algorithm which was introduced by Kennedy on the basis of swarms. There are certain features in PSO that are also found in other mutative algorithms. The system is set to begin with number of inhabitants. After that, the searching process is performed to search for targets[18]. In contrast to GA, PSO has no operators such as fitness, mutation, etc. In PSO, every single constituent part of PSO proceeds after another particle in its space in order explores new solutions. Every constituent part of PSO possesses individual coordinate and velocity and they proceed further through the search space. Each particle has vector x, that is proceeding with velocity b. Suppose that the search space is m-dimensional, then o^{th} . An individual can be represented as[19];

$$X_o = \{ X_o1,\ X_o2, \ldots\ldots\ldots\ldots X_om\}$$

$$V_o = \{ V1,\ V_o2, \ldots\ldots\ldots\ldots V_om\}$$

O=1, 2, 3............m.

Where m is the size of the swarm population. Previous experience can be represented as below;

$$A_{of}\_f = \{ A_{of}\_f1,\ A_{of}\_f2 \ldots\ldots\ldots A_{of}\_fm\}$$

The PSO algorithm can be represented as below;
Create initial particles.
Evaluate the objective function of each particle.
Choose new velocities
Update each particle location.
Iterate until a solution is reached.

2.3 Bacterial Foraging Optimization (BFO)

BFO algorithm was initially introduced in 2002 by Passino[20-26]. It is primarily inspired by the foraging and Chemotactic nature of microorganisms, particularly the bacteria i.e. Escherichia coli (E. coli). While the progression of actual bacteria forging over the tensile flagella set, locomotion can be accomplished. BFO technique is based on natural selection that tends to eliminate animals with poor foraging strategies. After many generations, poor foraging strategies are eliminated while only the individuals with good foraging strategy survive signifying survival of the fittest. BFO formulates the foraging behavior exhibited by E. coli bacteria as an optimization problem. Over certain real-world optimization problems, BFO has been reported to outperform many powerful optimization algorithms in terms of convergence speed and final accuracy[27].

3. Proposed Simulation Model

Quality of service optimization is considered as a very serious problem in wireless sensor network. In order to subdue these problems, a proficient cluster head is carefully chosen by utilizing cluster head selection algorithm to pick the CH systematically, which in turn leads to rise in the overhead. If some of the CH nodes are heavily loaded, then their energy will be rapidly consumed. Therefore, load balancing is introduced over clusters in order to accomplish undeviating energy consumption. Subsequently, on the accomplishment of the cluster formation along with the load balancing result, discovering the ideal route path becomes significant for the above results to decrease the time and discover the finest result. Routing the ideal path by employing the optimization techniques, results in lessen the time complication and creates the finest routing path in WSN. The simulation model of the work is shown in Figure 1.

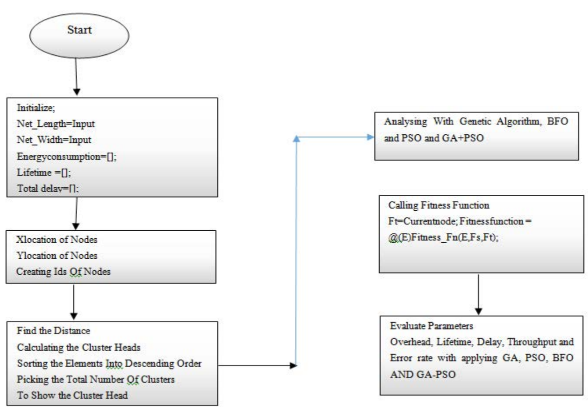

Figure 1. Flow chart of proposed simulation model.

Algorithm 1: Energy Optimization

Node Count=Input
Simtime=Input
Net Length=Input
Net Width=Input
Energy consumption=[];
Lifetime =[];
Total delay=[]
Location of Nodes
Location of Nodes
Creating Ids of Nodes
Energy Consumption
X Location of the Source
X Location of the Destination
Energy Chs=Energy Of nodes (sort, 'Descending);
Select highest energy nodes as required cluster heads
Chcount= nlog(nodes)/log(2)

The algorithm described above explained the method to discover the energy of a CH node existing in the network.

Algorithm 2: Data Transmission

Data Will Be Transferred Directly
Find the Coverage Set Of Each Node from Others
Find the Distance
Calculating the Cluster Heads
Sorting the Elements Into Descending Order
Picking the Total Number of Clusters
To Show the Cluster Head
Now As the Source and Destination Is Decided, the Source Will Look, For the Closest Cluster Head to Proceed and Will Repeat the Process, Till the Destination Is Not Found
Finding the Closest Cluster Head to the Source.
Finding the Nearest Cluster Head in the Coverage Set of the Plotting Cluster Generated Path

Above algorithm describes the process to find the distance between the sources nodes to destination node present in the network to do transmission of data.

Algorithm 3: Utilization of Genetic Algorithm, PSO, BFO

Analyzing With Genetic Algorithm
Calling Fitness Function
Ft=Current node; Fitness function = @(E)Fitness Fn(E,Fs,Ft);
Plotting Cluster Generated Path
Analyzing With PSO Algorithm
Maximum Probability
Best value so far
Initial velocity
Evaluating position & quality
Update x position
%update y position
Fitness evaluation (can change according to the requirement)
% if new position is better
% update best x,

% best y positions
{Evaluate Parameters
% and best value
Bfo initialization (Call when required) if time > threshold and energy consumption <theta
Global best position
Lifetime a=Lifetime;
Delayga=Total delay;
Throughputga=Throughput;
Roverheadga=Routing ovr Itr;
Error=Error Rate Itr;
End}

The algorithm presented above represents the process of optimization on the basis of GA, PSO and BFO in order to discover the optimum distance among the source and destination. These optimization methods work on the fitness function. Every individual generation is made up of the population as revealed in the flowchart whereas; every individual within the population denotes the search space or probable result. Moreover, every individual in population ultimately leads to the further development. It executes as Initializing arbitrary population comprises of chromosomes, and then the fitness function in the population is calculated. Establish new population comprises of individual entities. Selection process issued for selecting paternal chromosomes in order to acquire the optimum fitness function. The algorithm also utilized BFO when the time span is more than the threshold i.e. ample time is provided and also the energy available is more than the demanding energy only then BFO can be opted.

Hybrid Algorithm (GA + PSO)

The hybrid algorithm is considered to optimize the total performance of the network. The hybrid algorithm is planned in such a way that the preliminary route selection will be achieved by Genetic Algorithm and later PSO Algorithm is implemented in order to optimize the performance of our algorithm. The architecture of the algorithmic is as follows:

Function optimized Route= Optimize Hybrid (Nodes. architecture)
All x=Node. Architecture. X
All y= Node. Architecture. Y
Cove range=[ ];
For i=1: Total Nodes
For j=1:Total_Nodes
Dist = sort ((all x (i)-all x(j))^2 +(all y(i)-all y(j))^2)
End for
End for
Identify source( );
Identify destination ( );
Initial population ga= Node. Count;
mutation_initial_value=.5
cross over=" linear";
Ga. optimised= {Population, Mutation, Crossover, fitness function}.
Find Node next hop =ga.fitness. Value();
If node. Fitness accepted
Add node to path;
End if
If (Path.finalized)
Title= length.Path();
For i=1: title
Initialvelocity = random;
Initial displacement=random;
Find_pso_fit(initial,velocity,initial_displacement,route_path_elements)
Find_best_fit (pso fitness)
If satisfied (sendpacketthrough)
End if
End for
End function

4. Results and Analysis

For the design of our approach, two well-known metaheuristics: GA (genetic Algorithm) and PSO (Particle Swarm Optimization Algorithm) are considered. In order to optimize the QOS of Wireless Sensor Network, various algorithms and protocols are used and their comparisons are used through routing. In this paper, study of applications with GA and PSO is done with the enhancement i.e. hybridization of GA and PSO. The entire simulation has been accomplished in MATLAB 2010a, by utilizing the parameters: Network lifetime, End to end delay, Throughput, Routing overhead and Bit error rate as depicted in Table 1.

Throughput is primarily defined as the maximum rate of creation or the rate at which an item can be treated while utilizing the throughput in the context of communication networks. Bit error rate (BER) can be explained as the rate at which the errors occur during the transmission of the data packets within the communication network. End-to-end delay usually implied to the time taken by a data packet in migrating from source to the destination and vice versa[28]. It is simply defined as the time elapsed until a demanded route is available. It is expressed in milliseconds (ms). Network lifetime is defined as the time interval that a network can operate prior to its first node failure. Routing overhead arises due to the traffic occurred in the network while transmitting the data from source to destination. The plotting of WSN is depicted in Figure 2 with sensor nodes with height of 1000 m and width of 1000 m.

Table 1. Simulation Parameters

Number of nodes	100
Network length	1000m
Network Width	1000m
Parameters	Throughput, End to End delay, Error rate, Network lifetime, Routing overhead.
Algorithms	Genetic algorithm, Particle swarm optimization algorithm, BFO, GA-PSO
No. of iterations	100

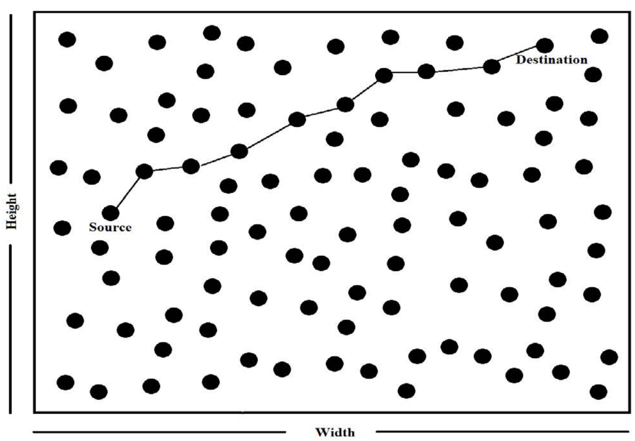

Figure 2. Plot of WSN.

4.1 Comparison of GA, PSO, BFO and Hybrid of GA-PSO Algorithms

Figure 3 shows the comparison chart of delay calculated in GA, PSO, BFO and Hybridization of GA and PSO algorithms. Delay normal is basically the minimum delay in the network while the transmission of the data packets. From the above diagram, it has been seen that value of delay with GA optimization is calculated as 11.9848, with PSO optimization it is 13.6548, with BFO optimization it is 8.6626 and delay is minimum in the hybridization of GA-PSO which is 0.1221. It is the average time taken by data packet to reach the destination from the source and contains the entire number of delays triggered by buffering during the route discovery expectancy, lining up at the interface queue. The figure presented above depicts the delay values with utilizations of GA, PSO, BFO and GA-PSO hybrid optimization.

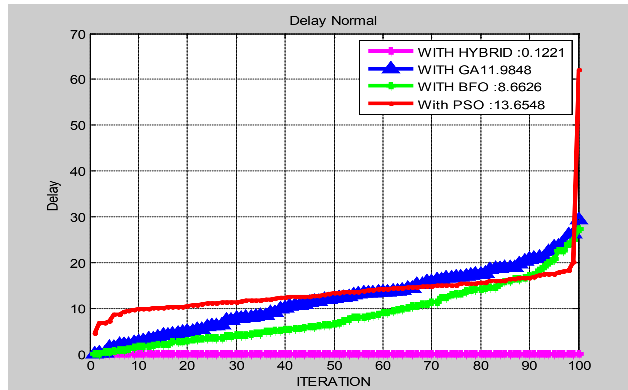

Figure 3. Comparison of Delay in GA, PSO, BFO, Hybrid (GA-PSO).

Figure 4 shows the comparative chart for the error rate calculated in GA, PSO, BFO and Hybridization of GA and PSO algorithms. It is again seen in the diagram that error rate is calculated very less in GA-PSO that is 12.1636 as compared with error rate calculated in GA which is 13.5151, in PSO it is 33.0517, in BFO it is 15.0074. Error rate is the total number of errors that occurs over the entire network within a specific time period during transmission of the data packets.

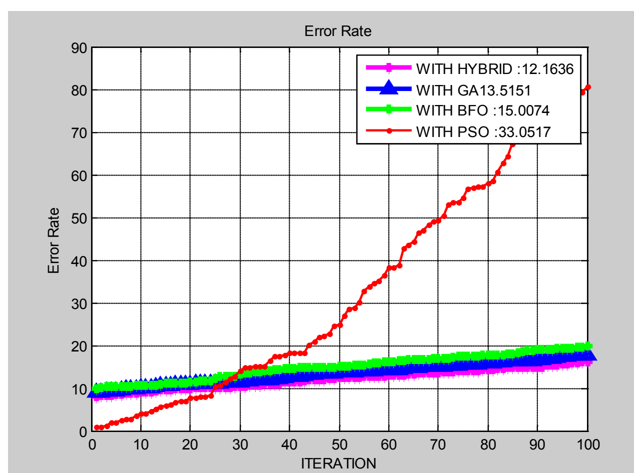

Figure 4. Comparison of Error-rate using GA, PSO, BFO and Hybrid (GA-PSO).

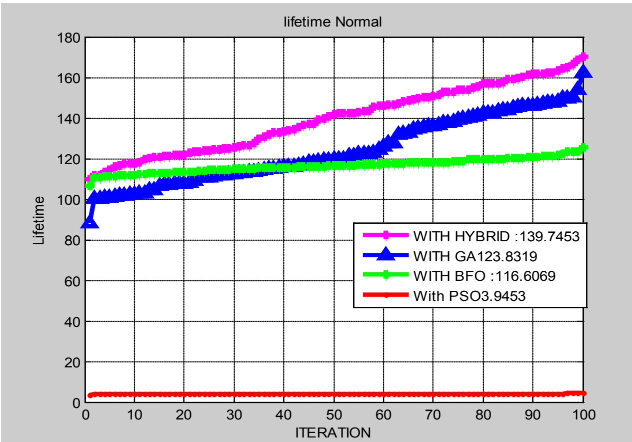

Figure 5. Comparison of Lifetime using GA, PSO, BFO and Hybrid (GA-PSO).

The comparison of lifetime by means of GA, PSO, BFO and Hybrid algorithm is depicted in Figure 5 it is seen that Hybrid of GA and PSO is calculating lifetime as 139.7453 which is maximum out of other algorithms which are taken in this work. In GA optimization lifetime is calculated as 123.8319, in PSO it is calculated as 3.9453, in BFO it is calculated as 116.6069. Lifetime normal means the entire number of the nodes that are active until the data reception along with congestion. The above Figure depicts the value of the Lifetime normal with the implementation of GA, PSO, BFO and GA-PSO hybrid optimization. From the graph, it has been observed that the value of Lifetime normal is calculated maximum in hybridization of GA-PSO which is 123.8319.

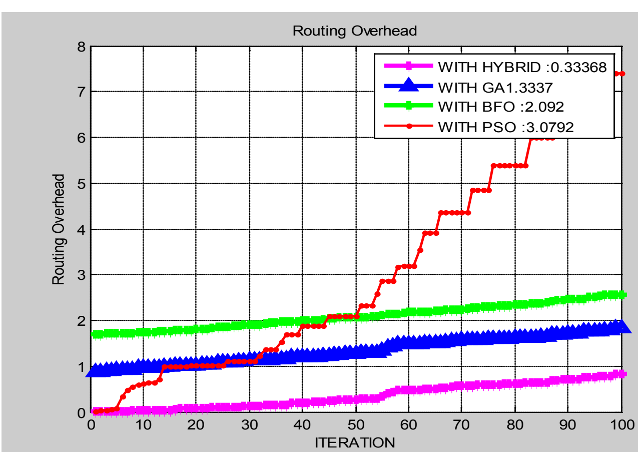

Figure 6. Comparison of Routing overhead using GA, PSO, BFO and Hybrid (GA-PSO).

Figure 6 shows the comparison chart of calculation of parameter Routing overhead which is calculated lowest 0.33368 in Hybridization of GA-PSO algorithm. Routing Overhead is the total numeral of nodes that are directed over the network in a specific time along with congestion. The above graph displays the value of the overhead with the implementation of GA, PSO, BFO and GA-PSO hybrid optimization. From the above figure, it has been observed that the average value of Routing overhead is calculated to be 1.3337 in GA optimization, 3.0792 in PSO and 2.092 in BFO optimization technique.

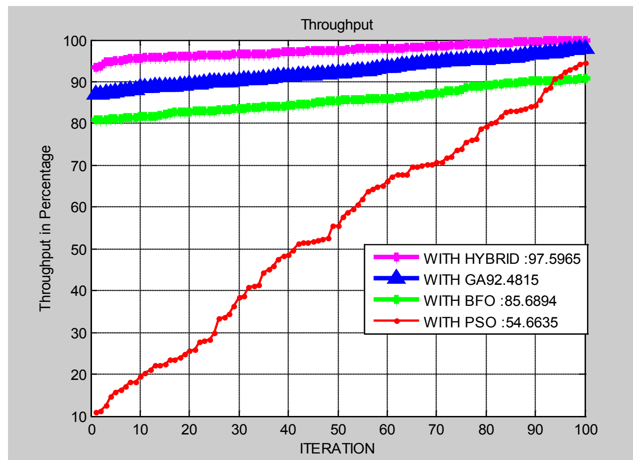

Figure 7. Comparison of Throughput in GA, PSO, BFO, Hybrid (GA-PSO).

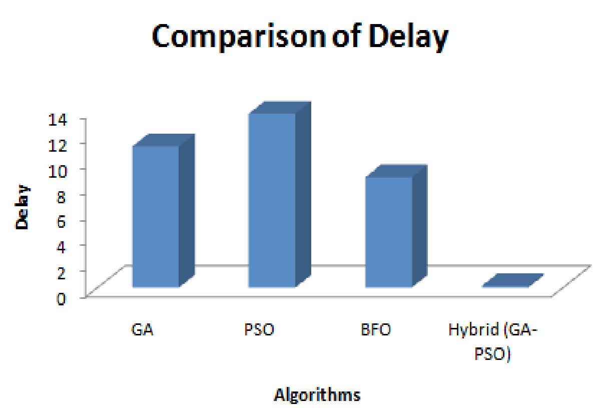

Figure 8. Comparison of Delay.

The comparison chart for throughput calculated in different algorithms as further it shows maximum throughput is calculated in hybridization of GA-PSO which is 97.5965 and is shown in Figure 7 throughput meant by the total number of nodes sent over the network for a specific interval of time with congestion from the source to destination. The above figure predicts the average value of the throughput along with the utilization of

Table 2. Calculated Delay, Error-rate, Lifetime, Routing overhead and Throughput by using GA, PSO, BFO and GA-PSO

Parameters	GA	PSO	BFO	Hybrid (GA-PSO)
Delay	11.09848	13.6548	8.6626	0.1221
Error-rate	13.5151	33.0517	15.0074	12.1636
Lifetime	123.8319	3.9453	116.6069	139.7453
Routing overhead	1.3337	3.0792	2.092	0.3368
Throughput	92.5965	54.6635	85.6894	97.5965

GA optimization, which has been calculated as 92.4815, In PSO it is 54.6635, In BFO it is 85.6894. The results being obtained for delay, Error-rate, Lifetime, Routing overhead and Throughput by using GA, PSO, BFO and GA-PSO are shown in Table 2. The comparison of delay for algorithms is shown in Figure 8. In the same fashion, the comparison of Error rate, lifetime, routing overhead and throughput is shown in Figure 9-12.

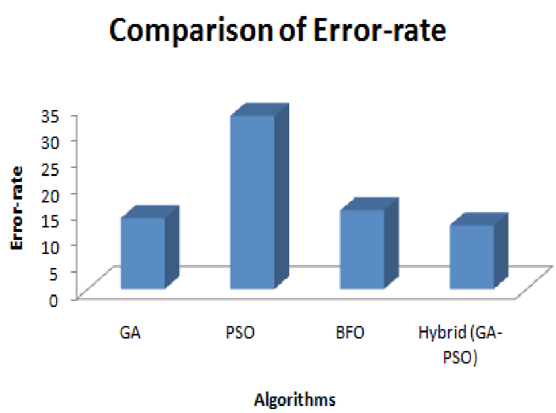

Figure 9. Comparison of Error rate.

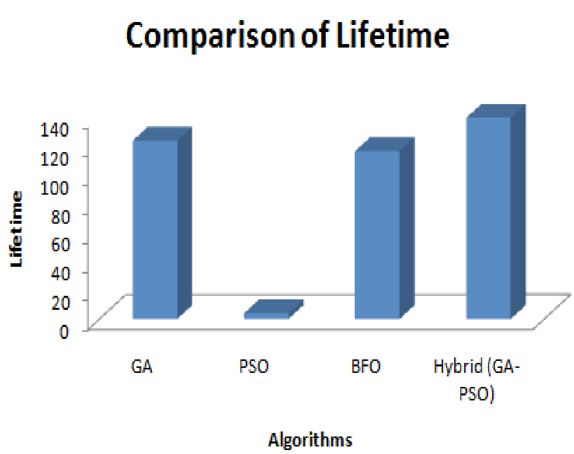

Figure 10. Comparison of Lifetime.

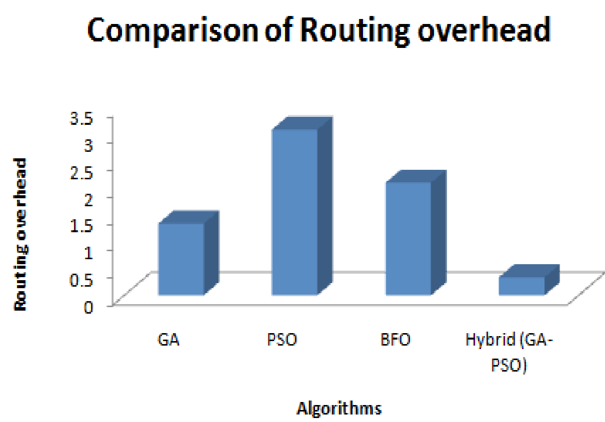

Figure 11. Comparison of routing overhead.

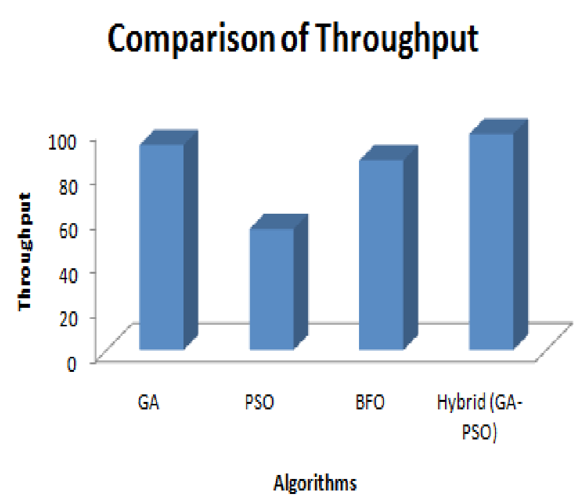

Figure 12. Comparison of Throughput.

5. Conclusion

The main aim of this proposed work is to give the comparative study of the GA, PSO, BFO and GA-PSO optimization techniques. As a result we find that the hybridization of GA and PSO optimization techniques performs better on the network performance parameters like Network lifetime, End to end delay, Bit error rate, Throughput and Routing overhead which evaluates the performance of wireless sensor networks by applying these optimization techniques. We find that the hybrid based optimization where GA and PSO are hybridized performs better than other algorithm so that the packets should reach from source to the destination with less packet drop rates and high data rates to extend the network lifetime. Here we find delay is significantly reduced in hybridization of GA-PSO techniques and calculated as 0.1221, network life time is increased by significant value and calculated as 139.743; whereas throughput is also enhanced in hybrid algorithms. Other parameters like error rate and routing overhead are also improving in proposed hybrid algorithm. Our proposed technique is very helpful for the convenient working of nodes which results as a high throughput, lower routing overhead, less error-rate, less end to end delay and improving network lifetime for the efficient transfer of packets from source to the destination. Future scope lies in the utilization of any other optimization algorithm to deploy the same existing problem of load balancing.

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