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Article

Genetic-Chicken Swarm Algorithm for Minimizing Energy in Wireless Sensor Network

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Abstract: Wireless Sensor Network (WSN) technology is the real-time application that is growing rapidly as the result of smart environments. Battery power is one of the most significant resources in WSN. For enhancing a power factor, the clustering techniques are used. During the forward of data in WSN, more power is consumed. In the existing system, it works with Load Balanced Clustering Method (LBCM) and provides the lifespan of the network with scalability and reliability. In the existing system, it does not deal with end-to-end delay and delivery of packets. For overcoming these issues in WSN, the proposed Genetic Algorithm based on Chicken Swarm Optimization (GA-CSO) with Load Balanced Clustering Method (LBCM) is used. Genetic Algorithm generates chromosomes in an arbitrary method then the chromosomes values are calculated using Fitness Function. Chicken Swarm Optimization (CSO) helps to solve the complex optimization problems. Also, it consists of chickens, hens, and rooster. It divides the chicken into clusters. Load Balanced Clustering Method (LBCM) maintains the energy during communication among the sensor nodes and also it balances the load in the gateways. The proposed GA-CSO with LBCM improves the lifespan of the network. Moreover, it minimizes the energy consumption and also balances the load over the network. The proposed method outperforms by using the following metrics such as energy efficiency, ratio of packet delivery, throughput of the network, lifetime of the sensor nodes. Therefore, the evaluation result shows the energy efficiency that has achieved 83.56% and the delivery ratio of the packet has reached 99.12%. Also, it has attained linear standard deviation and reduced the end-to-end delay as 97.32 ms.

Keywords: Energy efficiency; sensor nodes; chicken swarm optimization; load balanced clustering method; wireless sensor network; cluster heads; load-balancing; fitness function

1 Introduction

Wireless Sensor Network (WSN) in general consists of a huge amount of sensor nodes that are monitored and guarded by the Base Station (BS). Data transmission, sensing devices, and processing are all significant processes underlying the sensor nodes, which consume very little power and are non-rechargeable. Because of these flaws, still readily available is a research gap in conditions of improving the power competence and extending network lifetime [1]. WSN sensors were subjected to an excessive amount of real-world data processing and monitoring, better environmental, industrial, and other monitoring [2].

WSN knowledge is capable of achieving far-fetched tasks in and around the surface of the soil. The overall remote systems transform the world into a smaller village inside the corporate world as a result of massive victory in WSN innovation and data message benefit [2]. WSN has accomplished an unused point of reference within the taking after fields such as natural observing, agribusiness, and designing huge numbers of beautifully fetched efficient sequence power-driven sensor hubs. They are given in ad-hoc remote individual region systems (WPAN), which include a workstation, a radio module, and a control deliver linked to it [3].

In today's environment of computing, information compilation is quick in developing and increasing subject. For those applications, the sensor nodes generate a simple and moderate resolution, especially in the ungracious and low-maintenance locations where traditional approaches are costlier. Wireless Sensor Networks (WSNs) has gotten a lot of concentration in current duration due to their hidden capacity and broad range of applications, including physical and ecological monitoring, battlefield surveillance, security, and disaster management [4].

A Wireless Sensor Network (WSN) is made up of a huge amount of low-power sensor nodes that are often deployed in a non-uniform manner throughout the monitored area. A WSN consists of a great quantity of low-power sensor nodes which are often deployed in a non-uniform manner throughout the monitoring area to detect the activities and compile the sensed data. These sensor nodes are small devices that may measure the occurrence of a variety of events, such as changes in physical measures such as temperature, volume, pressure, and so on, or movement of an item or environment across the sensing field [5,6].

The cluster of device nodes is one amongst the forceful ways for the reasonable power and has various edges over normal ways [7]. Various scientists have addressed the clustering because it will limit the redundant messages swapping among the sensor nodes. It is particularly useful for those applications that need measurability and is sort of helpful in information meeting. As a result, it can decrease the interferences and alter the load amongst the sensor nodes [8]. The overwhelming majority of the present techniques of clustering depend upon the selection of a cluster head from the applicable commonplace sensor nodes that integrate the cluster-ID [9], residual energy [10], degree of property [11,12].

The evolutionary optimization of algorithm is assessed as a Genetic Algorithm (GA). Darwinian growth and endurance of the fittest are the centre plans of GA. The process of GA has three stages; fitness, survivals, and reproductions in a processed way [13]. The CSO algorithmic program has varied groups and every cluster has one rooster, hens, and chicks. Every cluster fact is a fastened mistreatment of fitness values of the roosters, hens, and chicks. Here the simplest fitness values are provided to the roosters (chickens). The smallest amount of fitness values is given to the chicks. The bulk of the amount is engaged by hens and people fitness values are arbitrary within the cluster [14]. The proposed GA-CSO with Load Balanced Clustering Method (LBCM) helps to improve the balancing of the network load and also improves the lifespan of the network. The research helps to identify the solutions for:

1. How the genetic algorithm reduces the cost optimization?
2. How is the communication energy reduced between the clusters?
3. How the sensor node loads are balanced?

4. How do the less-energy gateways are used?

The proposed Genetic Algorithms and Chicken Swarm Optimization GA-CSO with Load Balanced Clustering Method (LBCM) help to develop the lifespan of the network, load balancing and power utilization. The major contributions of this study are provided:

1. Genetic Algorithms with CSO minimizes the balancing of the load in the network.
2. During communication, the proposed GA-CSO with LBCM method increases the energy efficiency.
3. The clusters are calculated by fitness function and solve the complex problems.

The remaining part of the research is written as follows: Section 2 briefs the study of existing Wireless Sensor Networks (WSN), Genetic Algorithms (GA), Chicken Swarm Optimization (CSO) and Load Balanced Clustering Method (LBCM). Section 3 describes the working principal of the proposed model. Section 4 evaluates the result and provides a comparative study on different algorithms. Section 5 states the conclusion of the research work.

2 Related Works

Several optimization techniques were created in early days for WSN in attempt to increase the efficiency of the network. However, this section covers a portion of WSN research that uses genetic algorithms. A new Genetic Algorithm (GA) built on occupied and topological programming was developed to overcome the problem of overall network splitting (GAEST). The two different multiplex methods, remaining energy, gene replacement model, overlap model, and grouping were the primary parameters taken into consideration in the specified technique [15]. In order to achieve the optimal shortest path by greatly reducing the power usage, a power cross routing algorithm, namely the Part, was proposed as Multi Objective Path Planner (MOPL) [16].

The article [17,18] enhanced the life span of the network, the writer-built across genetic algorithm which was the grouping of gluttonous process and both directional mutations. Many genetic optimization strategies for clustering were created in the history to enlarge the efficiency of the network. However, this part discusses a quantity of the genetic algorithm-based on clustering studies. The K-clustering algorithm is incorporated in this study. The Multi-Objective Genetic Algorithm (MOGA) was built for the enhancement of genetic characteristics so as to improve the efficiency network [19]. To make the network lifespan clustering model more accurate, the genetic algorithm and a Heterogeneous WSN (HWSN) network was used. With the concept of many data sinks, the optimal clustering (GAOC) protocol was established. Moreover, it aids in the prevention of the hop-spot issue on the network [20,21].

The gravitational emulation local search is an excellent way to increase the precision. In this study [22], the (GELS) method is integrated with the genetic algorithm. Then, to reduce the complexity, an interactive clustering-based genetic algorithm (ACGA) is urbanized. In article [23] the whole framework was affecting the detachment in order to ensure the long-term viability of renewable energy sources, and thus the work was combined with a fuzzy clustering model through a genetic algorithm [24].

The Fixed Parameter Tractable (FPT) method algorithm is selected for which entry each sensor node should be given to, resulting in more evenly distributed weight and power utilization in the middle of the gateways. On the previous supply, what about a direction-finding hierarchy for inter-cluster communication that can disperse the routing transparency across the nodes? The authors also suggested an FPT approximation technique with an approximation factor of 1.1 in [25], which is more accurate than the prior estimate factors reported for load balanced clustering method. The FPT approach is used to allocate the sensor nodes to gateways while limiting the maximum load of the gateways. To balance the power consumption of the nodes, a power sensitive direction-finding algorithm is utilized to find the ideal routing tree between the gateways and the sink. In [26], the same authors have looked at the another FPT approximation technique with a 1.1 approximation factor. A virtual grid communication with some cells of equivalent dimension is employed to make the FPT access method practicable in large-scale WSNs, with FPT access method being executed independently in each group.

The objective of energy efficiency in WSN networks is a pressing one. Further research has been performed to increase the network presentation in conditions of energy utilization, throughput, load evaluation, broadcast costs, small package mistake speed, and latency in order to reach this goal. However, for processing the enormous amounts of data, a quantity of studies has focused on the connectivity of network and data exchange. Both synchronous and asynchronous protocols have been planned to get better network connectivity in this research, each with its own set of benefits and drawbacks. Many academics have proposed approaches to increase the energy savings of the sensor node by modifying only a few of these technological properties [27–30].

Other research has looked into the load balancing problem in order to increase the energy efficiency by managing the congestion of the network and the redundancy of data. When multiple sensor nodes linked to the similar source transmit data at the similar occasion, the data received by the source becomes clogged or fails, resulting in the reception of delay sensitive data. In order to overcome the problem of data reception delay and the reduction in the network power consumption, load balancing techniques are used [31–36].

In the existing system, it works with Load Balanced Clustering Method (LBCM) and it provides the lifespan with scalability and reliability of the network. In the existing system, it does not deal with end-to-end delay and delivery of packets [37–41]. For overcoming these issues in WSN, the proposed Genetic Algorithm based on Chicken Swarm Optimization (GA-CSO) with Load balanced Clustering Method (LBCM) is used. Genetic Algorithm generates the chromosomes in an accidental way and then the chromosomes values are calculated by using Fitness Function. Chicken Swarm Optimization (CSO) helps to solve the complex optimization problems. It consists of chickens, hens, and rooster. Similarly, it divides the chicken into clusters. Load Balanced Clustering Method (LBCM) maintains the energy during the message between the sensor nodes and it balances the load in the gateways. The proposed GA-CSO with LBCM improves the lifespan of the network. Therefore, it minimizes the energy consumption and also balances the load over the network.

3 Proposed Methodologies

Energy consumption and Load-balancing are the most important issues in Wireless Sensor Network (WSN). Clustering techniques are widely used for load balancing in the application of WSN. In addition to that, it consists of gateways and sensor nodes. The information is collected from the sensor nodes and transmits to the base station. In the existing system, the LBCM uses gateways for communication with the sensor nodes and during the process of communication, it consumes more energy. The proposed Genetic Algorithms (GA) based on Chicken Swarm Optimization (CSO) with Load Balanced Clustering Method (LBCM) provides a unique ID to the gateways and the sensor nodes. Simultaneously, it enhances the power consumption and balances the load of the network. Fig. 1 shows the structural design of the proposed system.

Fig. 1 shows the Cluster Head (CH) nodes that are collected from WSN and then the features are selected on random basis using GA-CSO. Fitness function and LBCM are used for improving the optimal solution.

3.1 Genetic Algorithm (GA)

A genetic algorithm is looked for heuristic based on the natural assortment hypothesis of Charles Darwin. This method replicates the ordinary choice, in which the fittest individuals are chosen for reproduction process in order to create the following generation for children. Genetic Algorithm (GA) is classified from evolutionary optimization algorithm. Besides, it consists of three stages such as fitness, survival, and reproduction [1].

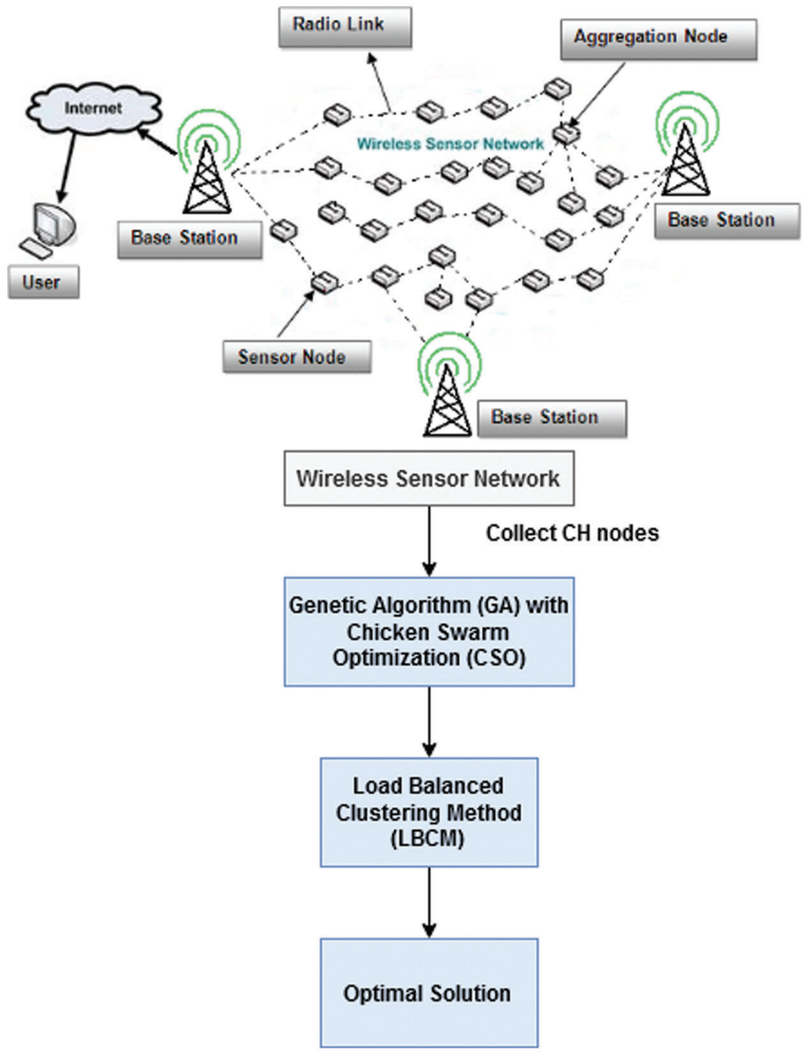

Figure 1: Architecture of GA-CSO and LBCM

Fig. 2 shows the process of genetic algorithm. Initially, the individual populations are generated. Individuals are then calculated by using fitness value. Genetic operators are used for individual selection and then the fitness calculations are processed in new individual. Finally, the current population is updated.

Algorithm 1 shows the initial process of GA that are randomly selected and then it is fixed in the initial population PN(K = 0). Similarly, the chromosomes are generated and then monitored. By using the values of chromosomes, the fitness function is calculated. The process continues until the fitness values are calculated. pmn(K) = 0.03 is represented as probability of mutation, pco(K) = 0.6.

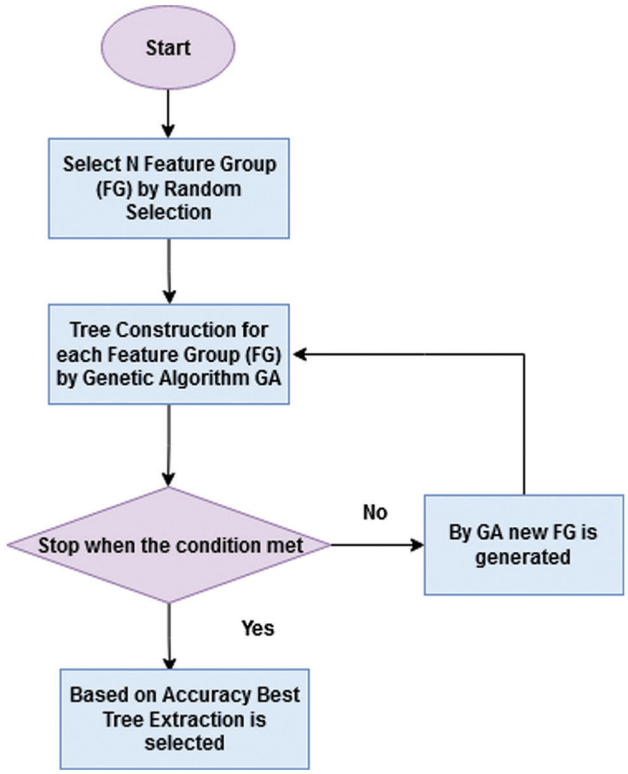

Figure 2: Genetic algorithm process

Algorithm 1: Pseudo code for Genetic Algorithm

```
Input: K, P(K)
Output: Best fit chromosomes
start
    initialize k = 0;
    p(k), random population is generated;
    fitness function is used for evaluating the fitness function;
while (condition is unsatisfied) do
      select P(K) from P(K−1)
      K = K + 1; \\ Increment in the initial population
      single point crossover is applied, pco(K) = 0.6;
      probability with mutation is applied, pmn(K) = 0.03;
      new offspring is updated
  end
  from cluster best fit chromosome is selected.
```

3.2 Load Balanced Clustering Method (LBCM) Algorithm

LBCM helps to group the sensor nodes all over the gateways. Along with that, it extends the life of the network by giving energy to the sensor nodes during the process of communication; also it balances the load among them. Algorithm 2 shows the LBCM process.

Algorithm 2: LBCM Algorithm

```
Input: Initialize the parameters i, j, k
Output: Average Eucledian Distance for deployed sensor nodes
1. for i = 1 to k do \\ no.of.gateways
            Euc_dis_Gwi = 0;
2. for j = 1 to n do \\ no.of sensor nodes
        Euc_dis_Gwi += Euc_dis(Gwi, sj);
        Gw_listi = (sj,Euc_dis(Gwj, sj);
      End
       avg_Euc_dis_Gwi = Euc_dis_Gwi/n;
     End
\\ initialize load for gateways
3. For i = 1 to k do
         LOAD[Gwi] = 0;
      End
\\ add nodes one by one into gateway
4. LBF = Ceil(sn/gx);\\ n is the no.of.sensor nodes and k is the no. of gateways
      For i = 1 to LBF do
         For j = 1 to k do
            If (Gw_listj(sj) ∉ LOAD(gwk)) then
               LOAD[Gwj] += Gw_Listj(sj);
            End
            Else
While (Gw_listj(++sj) ∉ LOAD[Gwx]) do
               LOAD[Gwj] += Gw_listj(sj);
            Break;
            End
         End
      End
End;
```

Within the clustering, it handles each gateway and calculates the normal Euclidean separate of the sensor nodes related with a door Gwi. The command in which the gateway start to join the sensor nodes of its cluster is the increment in the order of their normal Euclidean separate.

3.3 Proposed Genetic Algorithm (GA) Based on Chicken Swarm Optimization (CSO) and Load Balanced Clustering Method (LBCM)

The proposed GA-CSO with LBCM reduces the load balancing and also reduces the power utilization for the lifespan improvement of the network. In natural selection process, it contains two main stages; crossover and mutation, which help in the production of new generation. Moreover, it consists of three models. They are system model, energy model, and energy consumption model.

3.3.1 System Model

In this model, it contains Base Station (BS) and Sensors (n) and these help to maintain the standardized distribution based on the random consumption in the exposure region. The network details are described as follows:

- At the start, all nodes have the same amount of power. The BS has no power constraints and has a very high computing energy.
- Main cluster head (PCH) and minor cluster head (SCH) are selected on a regular basis based on the coverage area and localization.
- Nodes optimize the energy based on the transmission distance.
- Nap and get up node idea is implemented to reduce the energy usage in the network.
- Both cluster heads are multi-weighted allowing for a changing energy level to be maintained.
- Each node in the network has the ability to send its address information to its neighbour.
- BS and PCH are located inside the broadcast choice of the network.

In common, one-hop transmission has a significant impact on energy. As a result, p-jump is a superior option. The study, multi weight clustering will be explored, where the clusters are used to decrease the energy utilization and boost the power competence of WSNs.

3.3.2 Energy Model

In this model, there are two forms of power loss that are used; spacious energy defeat (D2) and multiple path declining authority loss (D4), and the channel model is chosen based on the transmission distance between the source and the sink. If the distance is less than the threshold value (Dth), the free space model is used as a channel model; otherwise, the multiple paths fading models are used as a channel replica. The following is a mathematical representation Eqs. (1) to (3) in the use of data energy based on the distance factor [21].

$$EN_{TX}(L,D) = \begin{cases} l \times EN_{energy} + L \times EN_{tm} \times D^2, if\ D \le D_{th} \\ l \times EN_{energy} + L \times EN_{am} \times D^4, if\ D \le D_{th} \end{cases} \tag{1}$$

EN_{energy} is represented as total power of the route per bit, EN_{tm} is represented as transmitter and ENaims denoted as the amplifier model of the network. Dth is the detachment of the threshold of the network.

$$D_{th} = \sqrt{\frac{EN_{tm}}{EN_{am}}} \tag{2}$$

Sink of the energy utilization is given as:

$$EN_{Rx}(L) = L * EN_{energy} \tag{3}$$

3.3.3 Energy Consumption Model

In this, the energy consumption model is explained [22]. The energy consumed by the transmitting node of L bits information to CH that is given in Eq. (4):

$$EN_{non-CH} = L* EN_{energy} + L* EN_{tm} D^2{}_{cn-CH} \quad (4)$$

Here, D cn-CH is represented as child node to cluster head distance.

The consumed energy of the cluster head is given as in Eq. (5):

$$EN_{CH} = \left(L\left(\frac{n}{c} - 1\right) * EN_{energy} + \frac{N}{2} * EN_{con} \right) + EN_{Rx}(L, D) + EN_{TX}(L, D_{CH-BS}) \quad (5)$$

Here, c is denoted as number of clusters in the network, n is denoted as number of alive nodes in the network, where ENRx is the cluster head of energy consumption; DCH-BS is represented as distance of base station to the cluster head.

3.4 Architecture of GA-CSO with Load Balanced Clustering Method (LBCM)

Developmental calculations have numerous categorizations, genetic algorithm is one among them which is motivated by the ordinary assortment method. Also, it comprises of two fundamental processes that is intersect and change with show era built-in to deliver long-standing time production. In genetic algorithm, a few people are shown so to choose the most excellent person and the intersect prepares is used. Fig. 3 shows the architecture of the proposed work.

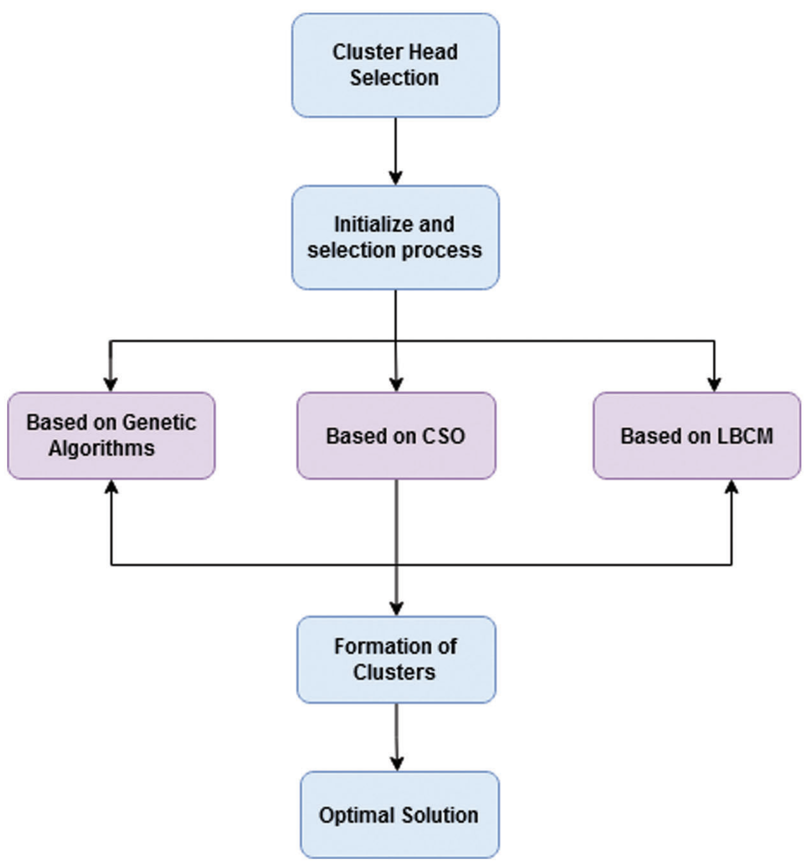

Figure 3: Architecture of GA-CSO with load balanced clustering method (LBCM)

Initially, the base station chooses the nodes as cluster heads, where each node is transmitted as a packet. The data and its address help to deliver the packet during the transmission. The CH selects the child nodes and then the fitness function is calculated. Thus, it is observed that the optimization algorithm is used to reduce the energy consumption.

Chicken Swarm Optimization

According to the actions of chickens and presentation of chicken swarm, the CSO is simulated. It may have several clusters and each cluster has a rooster, hens, and chicks [14]. By using fitness value, each cluster is fixed. Finest fitness principles are given to the chickens and the smallest amount of fitness principles are set to the chicks. Iteration of each instant of time is declared as G. Fig. 4 shows the flowchart of Chicken Swarm Optimization (CSO).

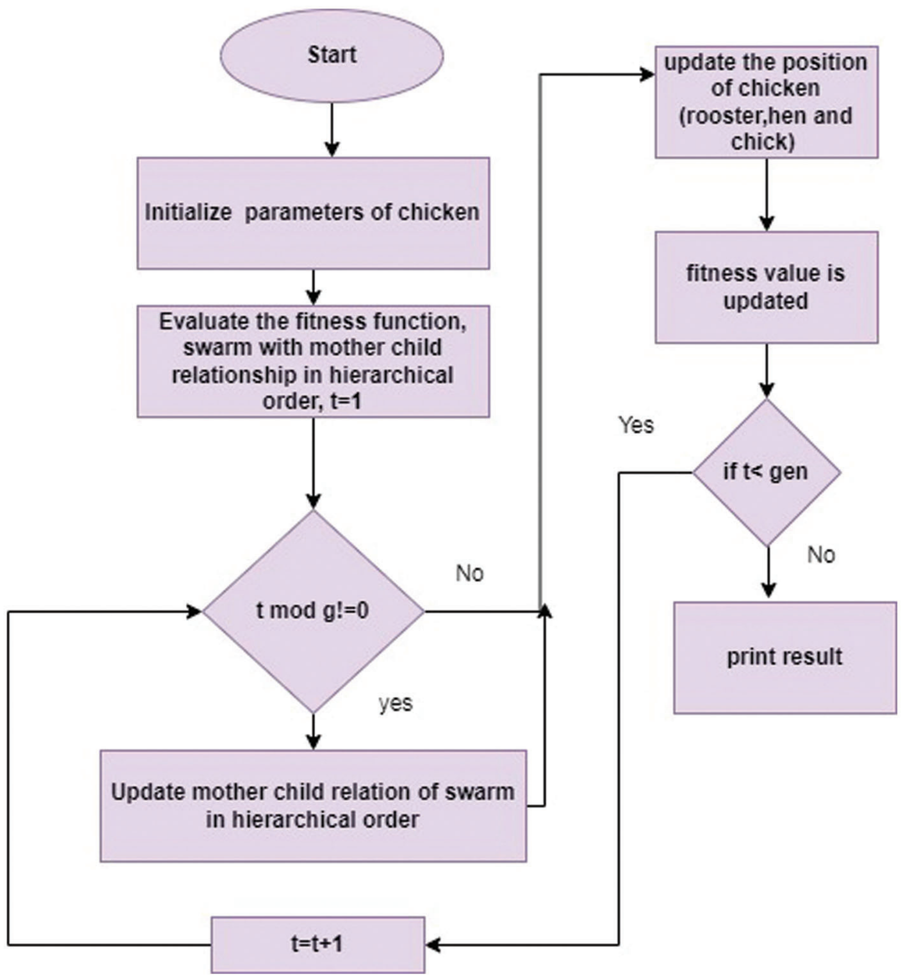

Figure 4: Flowchart of chicken swarm optimization

The ability of different members of the cluster is to search for food, which is rationalized based on the fitness principles of the first inhabitants, which is crucial to the group of hens. The following Eqs. (6) and (7) is a summary of the movement:

$$X_{i,j}^{t+1} = X_{i,j}^{t}(1 + randn(0, \sigma^2)) \tag{6}$$

$$\sigma^2 = \begin{cases} 1 & \text{if } f_i \leq f_K \\ \exp\left(\frac{f_K - f_i}{|f_i + \varepsilon|}\right) & \text{Otherwise} \end{cases} \tag{7}$$

Here $X_{i,j}^{t+1}$ is the roosteri position in jth measurement through t and t+1 iteration, where (0, σ^2) is denoted as Gaussian number, σ^2 is defined as standard deviation.

$$X_{i,j}^{t+1} = X_{i,j}^{t} + s_1 \times rand\left(X_{R1,j}^{t} - X_{i,j}^{t}\right) + s_2 \times rand(X_{R2,j}^{t} - X_{i,j}^{t}) \tag{8}$$

Then,

$$s_1 = \exp\left(\frac{f_i - f_{R1}}{abs(f_i) + \varepsilon}\right) \tag{9}$$

$$s_2 = \exp(f_{R2} - f_i) \tag{10}$$

R1 is denoted as index of the rooster and R2 is denoted as swarm chicken, it might be rooster or hen.

$$X_{i,j}^{t+1} = X_{i,j}^{t} + fl \times \left(X_{M,j}^{t} - X_{i,j}^{t}\right) fl \in [0, 2] \tag{11}$$

fl is represented as parameter, the chick follows its mother by parameter. ith is the position of the mother chick in $X_{i,j}^{t+1}$.

Algorithm 3: GA-CSO with LBCM

```
Input: G, CH(K), population size
Output: best optimal solution
start
        parameters are initialized CH(K), population size, G;
        population of the matrix is initialized
        fitness values are calculated
           While (t < gen);
              t = t + 1;
        K is divided into hens, rooster and chicks by utilising fitness function
         compute each row by using algorithm 2
         else
          give the solitary direct intersect and change the possibility
          replicate the process until the iterations reached the
      best solution that is occurred from the CH
end
```

Algorithm 3 shows the process of genetic algorithms based on chicken swarm optimization with load balanced clustering method.

4 Experimental Results

The proposed method Genetic Algorithms (GA) based on Chicken Swarm Optimization (CSO) with LBCM takes system model (NS-2) for evaluating the presentation of the system. It consists of C++ as a back end and TCL as a front end. In order to visualize the output, network animator (NAM) is used. For performance evaluation, trace files were used. Tab. 1 shows the simulation parameters and the values which are used. The parameters used for evaluation is energy efficiency, energy consumption, delivery ratio of the packet, standard deviation of the gateway, end to end delay.

Table 1: Simulation parameters and their values

Parameters	Values
Simulator	NS-2.34
Simulation period	90 ms
Coverage area	1100 * 1100
No.of nodes	150
Initial Energy	0.3 J
EN_{energy}	60 nJ/bit
Packet size	4500 bits

4.1 Energy Efficiency

In data transmission, the remaining energy is considered as energy efficiency. Fig. 5 shows the comparison of various protocols such as GA-LEACH, MWCSGA and GA-CSO-LBCM which is used for energy efficiency. It uses 150 nodes for the specified experiment. The proposed GACSO-LBCM has achieved 83.56%. The existing protocols GA-LEACH have 57.11% and MWCSGA has 79.32%. Hence, it is proven that the proposed algorithm has outperformed well than the existing protocols GA-LEACH, MWCSGA.

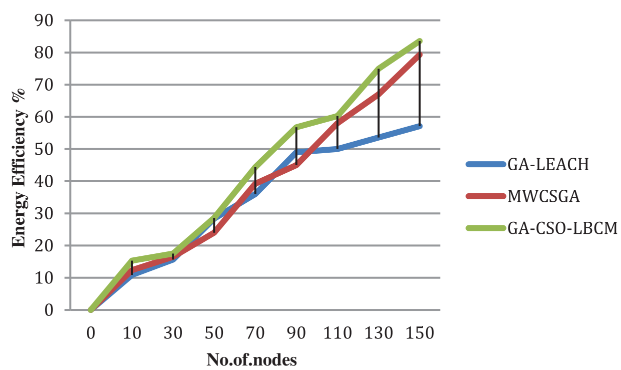

Figure 5: Energy efficiency

4.2 Delivery Ratio of the Packet

The delivery ratio of the packet is defined as the relation among the packets received by destination also, the packet sent by the sensor nodes. Fig. 6 shows the comparison of various procedures such as GA-LEACH protocol, Multi Weight Chicken Swarm based Genetic Algorithm (MWCSGA) and GA-CSO-LBCM which are used for calculating the delivery ratio of the packet. It uses 150 nodes for the proposed experiment. The specified GACSO-LBCM has achieved 99.12%. The existing protocols GA-LEACH have 78.36% and MWCSGA has 90.99%. Therefore, it is very clear that the proposed algorithm has outperformed better than the existing protocols GA-LEACH, MWCSGA.

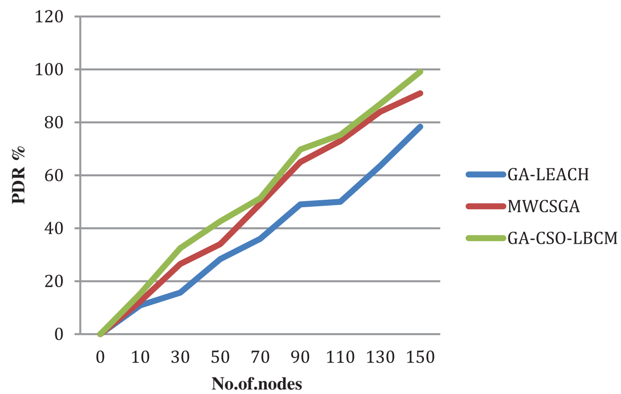

Figure 6: Delivery ratio of the packet

4.3 Standard Deviation of the Gateway

The standard deviation of the load in each gateway is calculated using different sensor nodes from 100-700. The gateways are constant during the experiment, it uses 10 cases. Fig. 7 shows the comparison of standard deviation between the different protocols such as GA-LEACH, MWCSGA and GACSO-LBCM. The proposed method achieves linear increase in the load between the gateways.

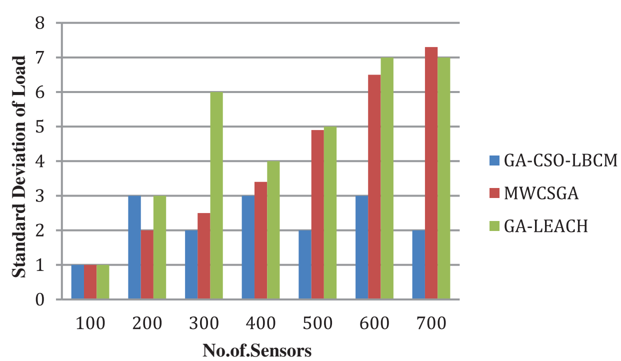

Figure 7: Standard deviation of the gateway

4.4 Calculation of End-to-End Delay

In general, the interruption of the network is defined as the end-to-end delay. Fig. 8 shows the comparison of various protocols such as GA-LEACH, MWCSGA and GA-CSO-LBCM which are used for calculating the end-to-end delay. Moreover, it uses 150 nodes for experiment. The proposed GACSO-LBCM achieves 97.32 ms.The existing protocols GA-LEACH have 275.12 ms and MWCSGA has 99. 86 ms.The proposed algorithm outperforms better than the existing protocols GA-LEACH, MWCSGA.

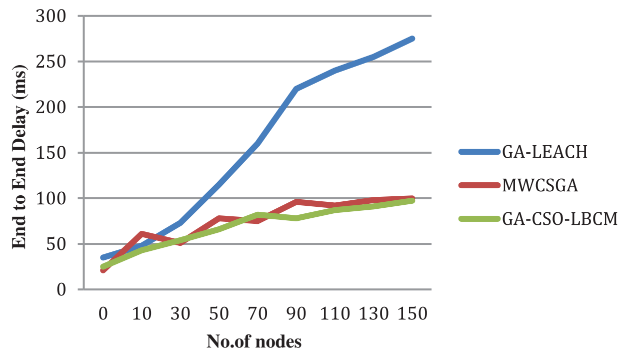

Figure 8: Calculation of end-to-end delay

5 Conclusion

Power consumption is one of the major problems in wireless sensor network. In order to overcome this problem, the proposed genetic algorithm-based chicken swarm optimization with load balanced clustering method is efficiently enhanced the energy consumption, the lifetime of the network during the process of communication in the system. There are many protocols used in the existing system such as GA-LEACH, MWCSGA that were compared with the existing system; thus, the proposed method outperforms well. The proposed GA-CSO with LBCM improves the lifespan of the network, it minimizes the energy consumption and also balances the load over the network. The proposed method outperforms by using following metrics such as energy efficiency, ratio of packet delivery, energy consumption, delivery ratio of the packet, standard deviation of the gateway, end to end delay. Therefore, the energy efficiency has achieved 83.56%, delivery ratio of the packet has reached 99.12%, it achieves linear standard deviation also it minimizes the end-to-end delay as 97.32 ms.

In future, to improve the lifespan of the network and to reduce the energy consumption machine learning and clustering techniques are used. For improving CH selection, several protocols should be used.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] N. Ajmi, A. Helali, P. Lorenz and R. Mghaieth, "MWCSGA—multi weight chicken swarm based genetic algorithm for energy efficient clustered wireless sensor network," *Sensors*, vol. 21, no. 3, pp. 791, 2021.

[2] H. Ahmad and N. Kohli, "LBCM: Energy-efficient clustering method in wireless sensor networks," *Engineering and Applied Science Research*, vol. 48, no. 5, pp. 529–536, 2021.

[3] C. Albaladejo, P. Sánchez, A. Iborra, F. Soto, J. A. López *et al.,* "Wireless sensor networks for oceanographic monitoring: A systematic review," *Sensors*, vol. 10, no. 7, pp. 6948–6968, 2010.

[4] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam and E. Cayirci, "Wireless sensor networks: A survey," *Computer Networks*, vol. 38, no. 4, pp. 393–422, 2002.

[5] A. A. Abbasi and M. Younis, "A survey on clustering algorithms for wireless sensor networks," *Computer Communications*, vol. 30, no. 14–15, pp. 2826–2841, 2007.

[6] M. Zhao, Y. Yang and C. Wang, "Mobile data gathering with load balanced clustering and dual data uploading in wireless sensor networks," *IEEE Transactions on Mobile Computing*, vol. 14, no. 4, pp. 770–785, 2014.

[7] I. Ahmed, M. Peng and W. Wang, "A unified energy efficient cluster id based routing scheme for wireless sensor networks-A more realistic analysis," in *Proc. Int. Conf. on Networking and Services (ICNS)*, Athens, Greece, pp. 86, 2007.

[8] O. Younis and S. Fahmy, "HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks," *IEEE Transactions on Mobile Computing*, vol. 3, no. 4, pp. 366–379, 2004.

[9] J. Yick, B. Mukherjee and D. Ghosal, "Wireless sensor network survey," *Computer Networks*, vol. 52, no. 12, pp. 2292–2330, 2008.

[10] M. Liu, J. Cao, G. Chen and X. Wang, "An energy-aware routing protocol in wireless sensor networks," *Sensors*, vol. 9, no. 1, pp. 445–462, 2009.

[11] W. R. Heinzelman, A. Chandrakasan and H. Balakrishnan, "Energy efficient communication protocol for wireless microsensor networks," in *Proc. Hawaii Int. Conf. on System Sciences (HICSS)*, Maui, HI, USA, 2, pp. 1–15, 2000.

[12] C. P. Low, C. Fang, J. M. Ng and Y. H. Ang, "Efficient load balanced clustering algorithms for wireless sensor networks," *Computer Communications*, vol. 31, no. 4, pp. 750–759, 2008.

[13] J. Arthur, R. Bahran, J. Hutchinson and S. A. Pozzi, "Genetic algorithm for nuclear data evaluation applied to subcritical neutron multiplication inference benchmark experiments," *Annals of Nuclear Energy*, vol. 133, no. 2, pp. 853–862, 2019.

[14] W. Osamy, A. A. El Sawy and A. Salim, "CSOCA: Chicken swarm optimization based clustering algorithm for wireless sensor networks," *IEEE Access*, vol. 8, no. 12, pp. 60676–60688, 2020.

[15] J. Zhou, Q. Cao, C. Li and R. Huang, "A genetic algorithm based on extended sequence and topology encoding for the multicast protocol in two-tiered WSN," *Expert Systems with Applications*, vol. 37, no. 2, pp. 1684–1695, 2010.

[16] R. Bhardwaj and D. Kumar, "MOFPL: Multi-objective fractional particle lion algorithm for the energy aware routing in the WSN," *Pervasive and Mobile Computing*, vol. 58, no. 11, pp. 101029, 2019.

[17] J. Li, Z. Luo and J. Xiao, "A hybrid genetic algorithm with bidirectional mutation for maximizing lifetime of heterogeneous wireless sensor networks," *IEEE Access*, vol. 8, no. 4, pp. 72261–72274, 2020.

[18] Y. Zhang and Y. I. Wu, "Multiple sources localization by the WSN using the direction-of-arrivals classified by the genetic algorithm," *IEEE Access*, vol. 7, no. 8, pp. 173626–173635, 2019.

[19] D. Dutta, J. Sil and P. Dutta, "Automatic clustering by multi-objective genetic algorithm with numeric and categorical features," *Expert Systems with Applications*, vol. 137, no. 4, pp. 357–379, 2019.

[20] S. Verma, N. Sood and A. K. Sharma, "Genetic algorithm-based optimized cluster head selection for single and multiple data sinks in heterogeneous wireless sensor network," *Applied Soft Computing*, vol. 85, no. 6, pp. 105788, 2019.

[21] S. M. H. Daneshvar, P. A. A. Mohajer and S. M. Mazinani, "Energy-efficient routing in WSN: A centralized cluster-based approach via grey wolf optimizer," *IEEE Access*, vol. 7, no. 10, pp. 170019–170031, 2019.

[22] T. Mohammadpour, A. M. Bidgoli, R. Enayatifar and H. H. S. Javadi, "Efficient clustering in collaborative filtering recommender system: Hybrid method based on genetic algorithm and gravitational emulation local search algorithm," *Genomics*, vol. 111, no. 6, pp. 1902–1912, 2019.

[23] T. He, D. Li and S. W. Yoon, "An adaptive clustering-based genetic algorithm for the dual-gantry pick-and-place machine optimization," *Advanced Engineering Informatics*, vol. 37, no. 7, pp. 66–78, 2018.

[24] Q. Wang and X. Yang, "Investigating the sustainability of renewable energy-An empirical analysis of European Union countries using a hybrid of projection pursuit fuzzy clustering model and accelerated genetic algorithm based on real coding," *Journal of Cleaner Production*, vol. 268, no. 3, pp. 121940, 2020.

[25] R. Yarinezhad and S. N. Hashemi, "Increasing the lifetime of sensor networks by a data dissemination model based on a new approximation algorithm," *Ad Hoc Networks*, vol. 100, no. 6, pp. 102084, 2020.

[26] R. Yarinezhad and S. N. Hashemi, "Solving the load balanced clustering and routing problems in WSNs with an fpt-approximation algorithm and a grid structure," *Pervasive and Mobile Computing*, vol. 58, no. 3, pp. 101033, 2019.

[27] Y. Zhang, X. Zhang, S. Ning, J. Gao and Y. Liu, "Energy efficient multilevel heterogeneous routing protocol for wireless sensor networks," *IEEE Access*, vol. 7, no. 3, pp. 55873–55884, 2019.

[28] A. Fanfakh, J. C. Charr, R. Couturier and A. Giersch, "Energy consumption reduction for asynchronous message-passing applications," *The Journal of Supercomputing*, vol. 73, no. 6, pp. 2369–2401, 2017.

[29] H. El Alami and A. Najid, "ECH: An enhanced clustering hierarchy approach to maximize lifetime of wireless sensor networks," *IEEE Access*, vol. 7, no. 12, pp. 107142–107153, 2019.

[30] M. Adil, R. Khan, M. A. Almaiah, M. Binsawad, J. Ali *et al.,* "An efficient load balancing scheme of energy gauge nodes to maximize the lifespan of constraint oriented networks," *IEEE Access*, vol. 8, no. 3, pp. 148510–148527, 2020.

[31] M. Abdel-Basset, R. Mohamed, N. M. AbdelAziza and M. Abouhawwash, "HWOA: A hybrid whale optimization algorithm with a novel local minima avoidance method for multi-level thresholding color image segmentation," *Expert Systems with Applications*, vol. 190, no. 1, pp. 116145, 2022.

[32] H. Seada, M. Abouhawwash and K. Deb, "Towards a better diversity of evolutionary multi-criterion optimization algorithms using local searches," in *Proc. of the 2016 on Genetic and Evolutionary Computation Conf. Companion*, Denver, USA, pp. 77–78, 2016.

[33] M. Abouhawwash and K. Deb, "Karush-kuhn-tucker proximity measure for multi-objective optimization based on numerical gradients," in *Proc. of the 2016 on Genetic and Evolutionary Computation Conf. Companion*, Denver, USA, pp. 525–532, 2016.

[34] M. Abouhawwash, M. A. Jameel and K. Deb, "A smooth proximity measure for optimality in multi-objective optimization using benson's method," *Computers & Operations Research*, vol. 117, no. 3, pp. 104900, 2020.

[35] S. T. Suganthi, A. Vinayagam, V. Veerasamy, A. Deepa, M. Abouhawwash *et al.,* "Detection and classification of multiple power quality disturbances in microgrid network using probabilistic based intelligent classifier," *Sustainable Energy Technologies and Assessments*, vol. 47, no. 4, pp. 101470, 2021.

[36] M. AbdelBasset, D. E. Shahat, K. Deb and M. Abouhawwash, "Energy-aware whale optimization algorithm for real-time task scheduling in multiprocessor systems," *Applied Soft Computing*, vol. 93, no. 2, pp. 106349, 2020.

[37] M. AbdelBasset, R. Mohamed, M. Abouhawwash, K. R. Chakrabortty and J. Michael, "EA-MSCA: An effective energy-aware multi-objective modified sine-cosine algorithm for real-time task scheduling in multiprocessor systems: Methods and analysis," *Expert Systems with Applications*, vol. 173, no. 3, pp. 114699, 2021.

[38] M. AbdelBasset, R. Mohamed and M. Abouhawwash, "Balanced multi-objective optimization algorithm using improvement based reference points approach," *Swarm and Evolutionary Computation*, vol. 60, no. 4, pp. 100791, 2021.

[39] H. Seada, M. Abouhawwash and K. Deb, "Multiphase balance of diversity and convergence in multiobjective optimization," *IEEE Transactions on Evolutionary Computation*, vol. 23, no. 3, pp. 503–513, 2019.

[40] M. Abouhawwash and A. M. Alessio, "Multi objective evolutionary algorithm for PET image reconstruction: Concept," *IEEE Transactions on Medical Imaging*, vol. 40, no. 8, pp. 2142–2151, 2021.

[41] N. Mittal, H. Singh, V. Mittal, S. Mahajan, A. K. Pandit *et al.,* "Optimization of cognitive radio system using self-learning salp swarm algorithm," *Computers Materials & Continua*, vol. 70, no. 2, pp. 3821–3835, 2022.