



SECURE DATA TRANSMISSION PROTOCOL USING NETWORK

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Abstract

Due to their expanding usage, any type of internet or even other networking technology communication must now be safe. For this aim, various security algorithms have been developed and used in the past. Attackers have found new ways to hack communication networks as just a result of such improvements. The wireless sensor network is made up to hundred or even thousands for small, energy-constrained sensors which is thickly distributed across the vast geographic area. Low Energy Adaptive Clustering Hierarchy (LEACH) has been shown to be an energy-effective routing strategy of Wireless Sensors Networks (WSN). The research develops unique hybrid swarm intelligent method of artificial bee colony (ABC) and particle swarm optimization (PSO). Information transfer is a very essential application in Device-to-Device (D2D) communication, and arithmetical results display that the suggested method is effective and improves performance than both Dragonfly Algorithms. However, because the connections is made direct on between proximity devices, it may be vulnerable to a range of security risks, including information alteration and fabrication, as well as privacy violations. The network is first organised into a number of rectangular regions, with one cluster head in each zone (CH). To choose cluster heads, a nature-inspired optimization technique is utilized, using remaining energy, median node to node distance, and distance from node to sink as the deciding factors. After calculating the centroid position of the CHs, the sink moves into the observation field. The result section shows the superiority of the suggested Different protocols over standard strategies in terms of network, packet delivery ratio, and packet delay.

1. Introduction

The Wireless Sensor Networks could use for creating reliable monitoring system that will transmit information over vast distances. These networks is known as information gathering networks because they allow users to

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retrieve high-level crucial information by correlating information. The major responsibility of the sensors nodes would be of gather environmental information and deliver the processed information to other node or the base station (BS) after primary processing. Sensors is typically constrained in energy supply, mobility, and bandwidth. Where battery recharge isn't always possible, sensor networks must be built to really be highly energy efficient in all aspects. Sensor nodes in clustered based networks is divided to numerous clusters, with each node belonging to just one cluster [1-6].

Energy efficiency is an important design concern in the WSN to improve the network's life lifetime. LEACH and LEACH-C is two common efficient routing algorithms. However, LEACH makes no guarantees about cluster head node placement or quantity, LEACH-C implies almost all node has worldwide network information, that is not always accessible and consumes a lot of energy [7-13]. We investigate in what way to build well-dispersed clusters with a fixed CHs quantity or a relatively close collection of CHs without global information to confirm that the overall energy debauchery of a sensors was stable and minimalized [14-17].

Particle Swarm Optimization (PSO) were created in 1995 by Eberhart and Kennedy and is based on the concept of social interface a bird swarm and a fish school. PSO starts with a population of generalised potential solutions that is generated at random. It seeks the best answer by forming swarms that follow the best particle. PSO are now the most broadly used SI procedures, with applications in optimization algorithms, traveling salesman problems, reproduction neural structure, occupation shop preparation problems, clustering problems, vehicle routing problems, multiple objective optimizations, and system control, among others. The artificial bee colony (ABC) algorithm was introduced SI method that was developed recently. Karaboga presented this innovative technique for numerical optimization based on the foraging behaviour of bee colonies. ABC has compensations in reminiscence, resident search, and resolution enhancement mechanisms, allowing it to get outstanding results for optimization problems and attracting a lot of interest in related research disciplines. By trying to introduce a constricted handling method, Karaboga as well as Basturk extended ABC from unrestrained optimization to constricted optimization problems; Chong et al. formed the bee colony optimization technique again for

the job shop agenda problematic; Wong and Chong developed effective ABC-built technique for the itinerant salesman problematic; Kang et al. applied ABC to structural opposite examination; Fithian et al. projected honey-bee breeding optimization clustering procedure problems [18- 21].

The multi-objective allowance approach, stages optimizing technique, dfp (davidon fletcher powell) technique, and goal programming technique is examples of non-evolutionary algorithms. The programming-based method is a very well of them. Route assessment GA technique, Multi-objective genetic algorithms, competitive collection inherited algorithm, non-dominated organization inherited algorithm, and others is examples of common evolutionary algorithms. Evolutionary algorithms have indeed been demonstrated to solve multi-objective problems successfully with random optimization or search approaches, but with inferior convergent haste more inclusion conflict than genetic algorithms.

2. Leach Cluster Head Algorithm

Each node in LEACH uses an iterative procedure to determine its status. This procedure is completed for each node when it both elects by itself with CH or discovers CH to join. Ciprob is set with the required percent of CHs between all sensor nodes at the start of this operation (5 percent). The likelihood to become CH (CHiprob) is set by each node as follows: $CHiprob = MAX(Ciprob * (iresidual/Emax), pimin)$ Eiresidual is present energy of the node, while Emax seems to be the max energy equivalent with the full battery in the equation above. It's important that the value of CHiprob must be less than pimin. The iterations of the While loop is limited to O by this threshold (1). The following is how SCH is defined: $SCH = Sdeterministic_CHi \cup Scandidate_CHi$, where $iSdeterministic_CHi = \{All\ deterministic_CHis\ from\ repetition\ 1\ to\ repetition\ i\}$ and $Scandidate_CH = \{All\ candidate_CHs\ since\ repetition\ 1\ to\ repetition\ i\}$. A node becomes candidate_CHi, deterministic_CHi, or even the member is joining other the CH during this process. By start, the node by greater energy (CHiprob) takes a better probability of becoming candidate CHi. When a node has become a candidate CHi, it informs the nodes in the cluster range of its new status. If the nodes have a advanced score than the additional candidate_CHis in its neighbourhood in the following iteration as well as its CHiprob reaches one,

its status changes to deterministic_CHi. After then, the nodes send deterministic_CHi message with all of their cluster neighbors.

Whenever the nodes that obtains a deterministic_CHi communication, on the other hand, it can no longer become a CH. As a result, scores of linked deterministic CHis, it must choose one of deterministic CHis in its neighbourhood. The node running this code double the amount of its CHi_{prob} at the end of the each loop iteration and moves onto next iteration. When the node's CH_{previous} value hits one, it stops performing the loop. As a result, nodes with more energy can complete this procedure faster. Nodes having a lesser quantity of remaining energy can remain normal after the execution and form the deterministic_CHi. The nodes finish the cluster process but have not yet conventional a deterministic_CHi communication, it uncovered and announces itself with a deterministic_CHi. It's worth noting that any deterministic CHi or candidate CHi could only send CHi_{msg} once in that process.

2.1. Leach Cluster Head Algorithm Process

1. $CH_{i\text{prob}} \leftarrow \text{Max} \left(C_i\text{prob} * \left(\frac{E_{i\text{residual}}}{E_m} \right) p_i \text{ min} \right)$
2. $is_{\text{deterministic}} - CH \leftarrow \text{False}$
3. *While* ($CH_{\text{previous}} \neq 1$) *DO*
4. If $S_{CH} \leftarrow \{ \text{Candidate } CHi \ is_{\text{deterministic}}_{CHi} \} \neq \emptyset$
5. If $S_{CH} \leftarrow \{ is_{\text{deterministic}}_{CHi} \} \neq \emptyset$
6. If (*node* $D = \text{MostScore}(S - CH_i)$ and $CH_i\text{prob} = 1$)

$$CH_{i\text{Msg}}(\text{NodeID}, s_{\text{deterministic}}_{CHi}, \text{Score})$$

$$\{ is_{\text{deterministic}}_{CHi} \} \leftarrow \text{True}$$
7. Else if $CH_i\text{prob} = 1$

$$CH_{i\text{Msg}}(\text{NodeID}, s_{\text{deterministic}}_{CHi}, \text{Score})$$

$$\{is_{deterministic_{CH_i}}\} \leftarrow True$$

8. Else if $Random(0, 1) < CH_i prob$

$$CH_{iMsg}(NodeID, s_{deterministic_{CH_i}}, Score)$$

$$CH_iPrevious \leftarrow CH_i prob$$

2.2. Simulation Result for Leach Algorithm Cluster

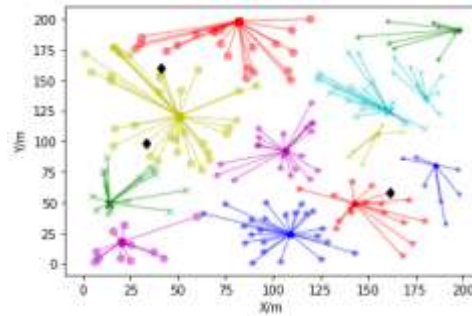
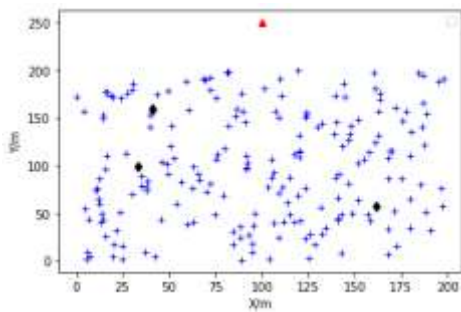


Figure 2 (1). System Model.

Figure 2 (2). Cluster Head for LEACH.

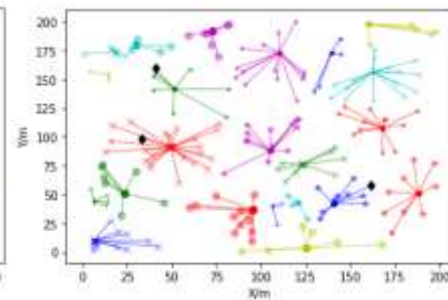
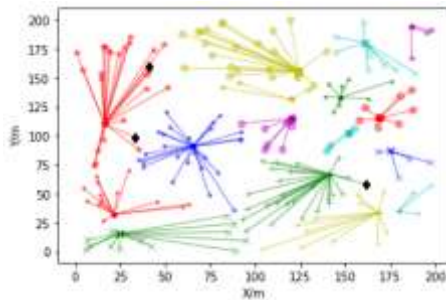


Figure 2(3) Cluster Head for LEACH. **Figure 2(4)** Cluster Head for LEACH

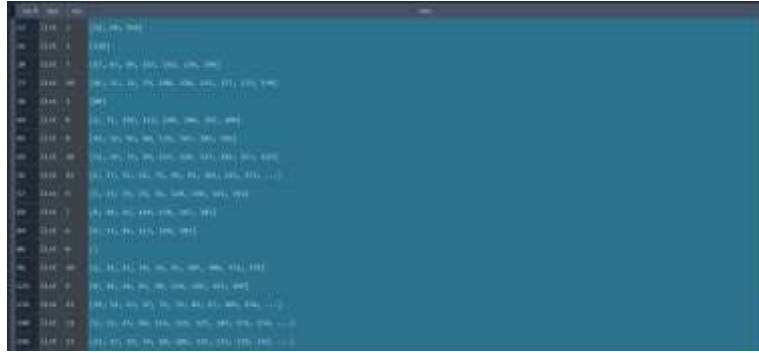


Figure 2 (5). Cluster and Node Values with Size.

3. Particle Bee Colony Swarm Algorithm

The PSO algorithm updates a particle's velocity based on its prior speed and the distances between its present position and its best place and the best position of the group. Parameter and random numbers is the constants of prior rate and two detachments, respectively. A number of inactivity weight answers remained presented and industrialized in prior research to increase the presentation of a PSO algorithm. Its random standards for the maximum adapted PSO algorithms, on other hand, is continuously produced by a uniform delivery in the $[0, 1]$ variety. The random numbers, of course, reflect those weights for two ranges used to update the particle velocity. These two distances having minimal effect on the new particle speed if the variety of random values is tiny, which means the rapidity could be efficiently raised adjusted the depart for local optimization. Expanding that range of random variables is important to increase the PSO algorithm's global optimization capacity. Some random values created by different probability density functions were investigated in this research to see how they affect the PSO algorithms. In contrast, the consistent PSO method is studied for comparison, with the random values set to 0.5. Experimentation of test functions in 3 additional directions is used to evaluate and comparison the performance of the PSO with various forms random variables.

3.1. Particle Bee Colony Swarm Algorithm Process. Each particle in the typical PSO algorithm represents a potential solution to the issue inside the search space. The location direction and velocity vectors of the α^{th} specific

can be described in D-dimensional space as $x_a(x_{a1}, x_{a2}, \dots, x_{aD})$ and $v_a(v_{a1}, v_{a2}, \dots, v_{aD})$ respectively. The position and velocity of the a^{th} particle is described as follow just after random initialization of particles,

$$v_a(t_i + 1) = wV_a(t_i) + C_{i1}r_{i1}(P_{i1} - x_{i1}(t_i)) + C_{i2}r_{i2}(P_g - x_{i1}(t_i))$$

$$x_i(t + 1) = x_i(t_i) + V_a(t_i + 1)$$

wherever w is inactivity weight, that used to regulate all the impact of preceding velocity just the limits; C_{i1} and C_{i2} 2 constants that regulate weights of P_{i1} represents a good former stance of the a^{th} individual and position of all particles in the current two independently generated random values that universally diapers the range $[0, 1]$. Particle swarm optimization pseudo code.

Step 1. initialize Population

Step 2. for $t = 1$: maximum Generation

Step 3. for $ii = 1$: population Size

Step 4. if $f_i(x_{ai}(t_i)) < f_i(p_a(t_i))$ then $p_a(t_i) = x_a, d(t_i)$

Step 5. $f_i(P_g(t_i)) = \min(f_i(P_g(t_i)))$

Step 6. end

Step 7. for $d = 1$: dimension Step

Step 8. $V_a d(t_i + 1) = wV_a(t_i) + C_{i1}r_{i1}(P_{i1} - x_{i1}(t_i)) + C_{i2}r_{i2}(P_g - x_{i1}(t_i))$

$$x_i(t + 1) = x_i(t_i) + V_a(t_i + 1)$$

Step 9. if $v_a, d(t_i + 1) > V_{\max}$ then $v_a, d(t_i + 1) = V_{\max}$ then

Step 10. else if $x_a, d(t_i + 1) > V_{\max}$ then $v_a, d(t_i + 1) = V_{\max}$ then

Step 11. end

Step 12. if $x_a, d(t_i + 1) > X_{\max}$ then $x_a, d(t_i + 1) = X_{\max}$ then

Step 13. if $x_a, d(t_i + 1) > X_{\max}$ then $x_a, d(t_i + 1) = X_{\min}$ then

Step 14. end

3.2. Multi Objective Greedy Algorithm

Step 1. Initialization: Using greedy policies, create an initial population. Set the maximum generation and POP size;

Step 2. Determine the biological generation. If the generation reaches a particular value that are number 50, the migration process starts; otherwise, proceed the following phase.

Step 3. Make a decision based on unique property.

Step 4. Greedy mutation then crossover. Adaptive cross then mutation are demonstrated below.

$$T_s = \begin{cases} T_{s1} - \frac{(T_{s1} - T_{s2})(fit' - \bar{fit}_{avg})}{\bar{fit}_{max} - \bar{fit}_{avg}}, & fit' \geq \bar{fit}_{avg} \\ T_{s1} & fit \geq \bar{fit}_{avg} \end{cases}$$

$$T_s = \begin{cases} T_{y1} - \frac{(T_{s1} - T_{s2})(\bar{fit}_{max} - fit)}{\bar{fit}_{max} - \bar{fit}_{avg}}, & fit' \geq \bar{fit}_{avg} \\ T_{y1} & fit \geq \bar{fit}_{avg} \end{cases}$$

fit' – largest fitness value.

fit' – fitness value of individual would be mutation.

Step 5. The New gen Calculator keeps adding one to the equation.

Step 6. Conduct a final inspection: Terminate this algorithm and output the answer whenever the terminal criteria is fulfilled. If not, proceed to the following step.

Step 7. Create a new people. Then go to the step 2.

3.3. Simulation of Particle Swarm Optimization Algorithm

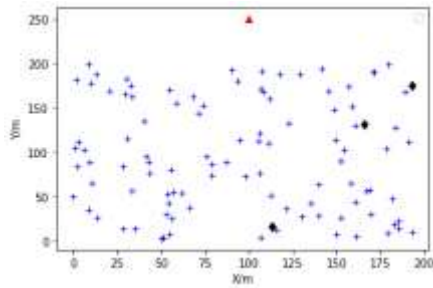


Figure 3 (1). System Model.

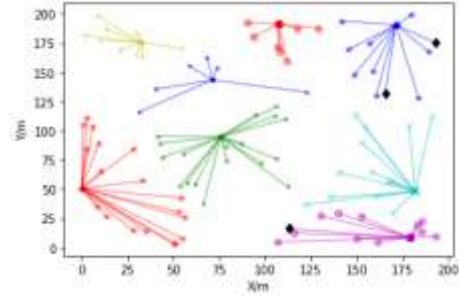


Figure 3 (2). Cluster Head for PSO.

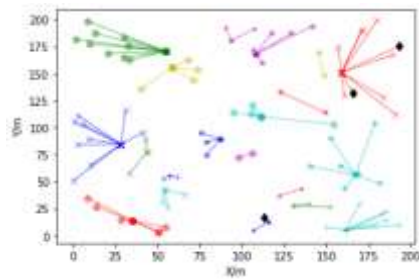


Figure 3 (3). Cluster Head for PSO.

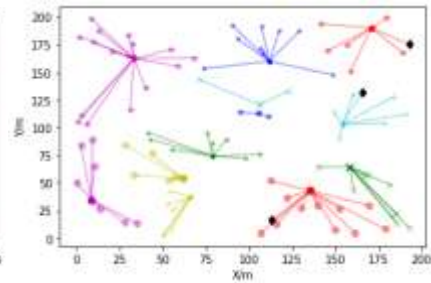


Figure 3 (4). Cluster Head for PSO.

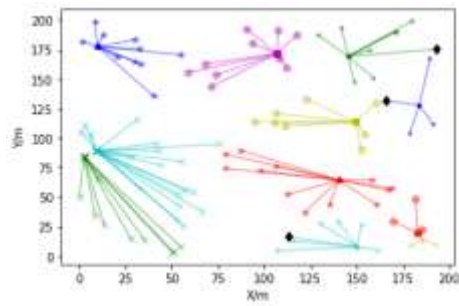


Figure 3 (5). Cluster Head for PSO.

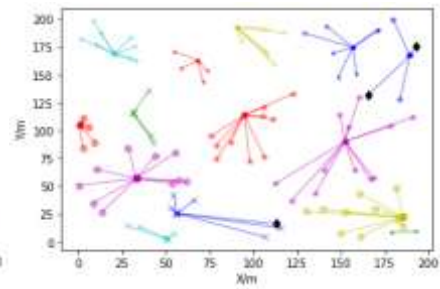


Figure 3 (6). Cluster Head for PSO.

```

In [ ]:
Out[ ]:
0
name      type      size
-----
0  list      1
1  list      100
2  list      100
3  DataFrame (100, 1) Columns names: Node
4  graph      graph      1
5  graph      graph      1
6  PSO        PSO        1
7  dict       dict       25

```

Figure 3 (7). PSO output with node and cluster representation.

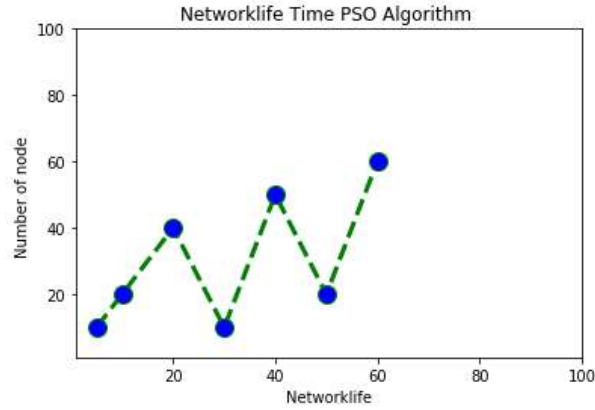


Figure 3(8). Performance Analysis –Network Life PSO.

4. Comparison of Existing Work and Proposed Work

```

#####
# # #
The number of Obj is: 18.388
1 0.011111111111111111
The number of Obj is: 18.388
2 0.125
The number of Obj is: 23.388
3 0.0228701285714286
The number of Obj is: 22.388
4 0.10490066666666666
The number of Obj is: 18.388
FindFont: Font family [ sans-serif ] not found. Falling back to DejaVu Sans.
Dragonfly Algorithm
Iteration of the starting population
Solution Fitness == 22.183418901996971, array == [5, 7, 5, 1, 2, 7, 1]
Solution Fitness == 33.642432748601787, array == [7, 6, 6, 5, 8, 5, 1, 10, 8, 10, 4, 10]
Solution Fitness == 48.83201114141414, array == [10, 8, 8, 2, 7, 7, 8, 8, 7, 8, 8, 2, 2, 8, 8, 8]
Solution Fitness == 46.7600946434721, array == [8]
Solution Fitness == 54.8021650889728, array == [10, 5, 8, 8, 7, 2, 1, 10, 8, 4, 3, 7]
Solution Fitness == 61.28018887899224, array == [8, 8, 8, 8, 8, 8, 2, 7, 2, 8, 8, 8, 7, 8, 8, 1]
Solution Fitness == 24.3090508889811, array == [2, 8, 3, 1, 10]
Solution Fitness == 72.14874889807481, array == [7, 1, 10, 8, 4, 8, 7, 8, 2, 8, 2, 2]
Solution Fitness == 22.1188423187883, array == [8, 8, 8, 8, 8, 8, 8, 7, 8, 3, 7, 8, 8, 8, 8, 1, 8, 2, 8]
Solution Fitness == 48.7987938227828, array == [1]
Solution Fitness == 45.1171888093381, array == [8, 8, 1, 2, 8, 7, 8, 10, 8, 1, 8, 5, 10, 6]
Solution Fitness == 18.04751115792881, array == [6, 1, 5, 10, 8, 5, 10, 7, 0, 2, 8, 9, 2, 3, 5, 4]
    
```

Figure 4 (1). Output of Dragonfly Algorithm.

```

#####
# # #
The number of Obj is: 12.388
1 0.011111111111111111
The number of Obj is: 1.388
2 0.125
The number of Obj is: 12.388
3 0.14285714285714286
The number of Obj is: 7.388
4 0.18890066666666666
The number of Obj is: 12.388
Choosing particles...
sheet: [3, 4, 2, 1, 0] | cost sheet: 9 | current solution: [3, 4, 2, 1, 0] | cost current solution: 9
sheet: [3, 8, 1, 2, 4] | cost sheet: 9 | current solution: [3, 4, 2, 1, 0] | cost current solution: 9
sheet: [3, 8, 1, 2, 4] | cost sheet: 9 | current solution: [3, 8, 1, 2, 4] | cost current solution: 9
sheet: [3, 8, 1, 2, 4] | cost sheet: 9 | current solution: [3, 4, 2, 1, 0] | cost current solution: 9
sheet: [3, 8, 1, 2, 4] | cost sheet: 9 | current solution: [3, 8, 2, 1, 0] | cost current solution: 9
sheet: [3, 8, 1, 2, 4] | cost sheet: 9 | current solution: [3, 8, 2, 1, 0] | cost current solution: 9
    
```

Figure 4 (2). Output of PSO Algorithm.

```

Solution : Fitness => 46.00246021090306, array => [1, 2, 1, 1, 0, 4, 8]
Solution : Fitness => 25.7351418250072933, array => [20, 6, 20, 2, 5, 4, 8]
Solution : Fitness => 27.542306423994993, array => [5, 2, 6, 1, 2, 7, 1]
Solution : Fitness => 35.01200181812066, array => [2, 6, 6, 1, 2, 7, 1]
Solution : Fitness => 37.407737817078688, array => [9, 4, 8, 2, 7, 7, 8]
Solution : Fitness => 37.348126399152218, array => [8, 4, 8, 20, 8, 7, 8]
Solution : Fitness => 39.07437712224926, array => [18, 3, 8, 8, 2, 2, 8]
Solution : Fitness => 35.10372665419012, array => [4, 3, 8, 8, 2, 4, 2]
Solution : Fitness => 38.906746634874, array => [2, 8, 3, 1, 10, 9, 7]
Solution : Fitness => 41.2947533866240, array => [1, 1, 10, 6, 4, 3, 7]
Solution : Fitness => 44.9038513999913, array => [8, 8, 9, 6, 8, 4, 8]
Solution : Fitness => 37.99984891158693, array => [1, 2, 8, 8, 3, 8, 8]
Solution : Fitness => 33.973288882378, array => [8, 8, 8, 2, 8, 7, 8]
Solution : Fitness => 34.8176048708600, array => [8, 2, 8, 18, 8, 9, 10]
Solution : Fitness => 38.0786537925164, array => [8, 3, 8, 8, 2, 2, 8]
Solution : Fitness => 38.20081582086608, array => [8, 9, 1, 8, 4, 4, 2]
Solution : Fitness => 34.1731555474836, array => [1, 6, 8, 8, 6, 5, 3]
Solution : Fitness => 38.303794234044787, array => [8, 3, 18, 8, 7, 3, 6]
Solution : Fitness => 34.2327148231123, array => [8, 3, 18, 8, 7, 3, 6]
Solution : Fitness => 34.9084248703556, array => [2, 2, 3, 4, 4, 0, 3]
Solution : Fitness => 38.41834778899803, array => [18, 8, 20, 2, 3, 4, 8]

Best node :
Solution : Fitness => 44.26303125998913, array => [6, 8, 9, 4, 0, 4, 8]
Warning! Beware! family 'best-eval' not found because none of the following families were found: Simul
    
```

Figure 4 (3). Cluster head formation and best possible.

```

# 0.14285714285714288
The number of Dn is: 7 388
# 0.14285714285714288
The number of Dn is: 13 188
forming particles...
gbest: [3, 4, 1, 1, 0] | cost gbest: 9 | current solution: [3, 4, 1, 1, 0] | cost current
solution: 9
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 4, 2, 1, 0] | cost current
solution: 9
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 6, 1, 1, 4] | cost current
solution: 9
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 4, 2, 1, 0] | cost current
solution: 9
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 6, 2, 1, 8] | cost current
solution: 10
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 6, 2, 1, 4] | cost current
solution: 10
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 4, 1, 1, 0] | cost current
solution: 10
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 6, 2, 1, 4] | cost current
solution: 10
gbest: [3, 4, 1, 2, 4] | cost gbest: 9 | current solution: [3, 4, 1, 1, 0] | cost current
solution: 10
gbest: [3, 4, 2, 1, 0] | cost: 9
    
```

Figure 4 (4). Cluster head formation and best possible node *f* node of Dragonfly Algorithm as gbest of PSO Algorithm.

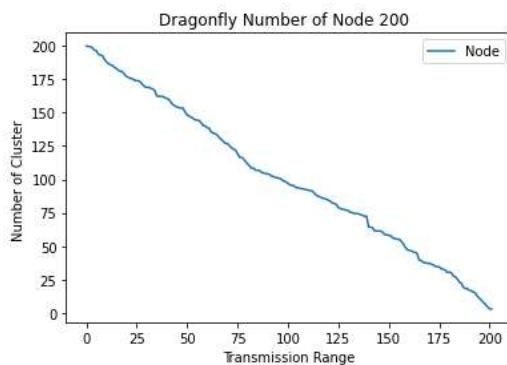


Figure 4 (5). Performance Analysis Energy Consumption Dragonfly Algorithm.

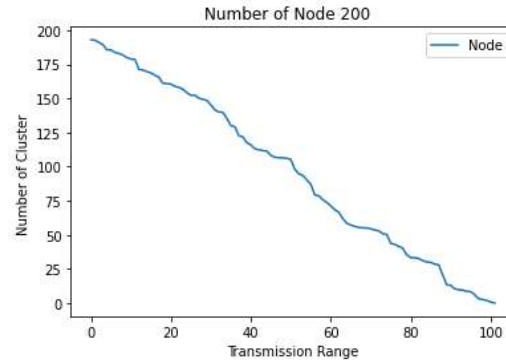


Figure 4 (5). Performance Analysis Energy Consumption PSO Algorithm.

As a result the has shown above, PSO and Dragonfly algorithm use same amount of node i.e. 200 but transmission range is different. Where in Dragonfly fitness value shows number of nodes it is taking and best possible path for information transmission is complicated where as in PSO gbest value shows number of nodes it is taking and best possible path for information transmission. Here LEACH is use for cluster head formation is PSO is use for getting best possible optimal path for information transmission.

5. Conclusion

We offer a unique Secure Information Transmission Protocol combining the LEACH Cluster Head algorithm and the Particle Bee Colony Swarm algorithms in this study. Cluster Heads is chosen based on residual energy of nodes and a multi-criteria score, and LEACH gives improved energy efficiency as well as an extended network lifetime. Regular nodes, on either hand, join the CH with the greatest score. An integrative swarm intelligence technique using particle swarm optimization as well as an artificial bee colony. For information exchange among particle swarm with bee colony, two information exchanging methods is established, one of which is thought to be able to improve the algorithm's performance. To test the effectiveness of the suggested strategy, numerical simulations is run. The suggested approach outperforms the existing Method in terms of numeric, graphic, and simulation results.

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