Proposing and Evaluating the Performance of PSO Intended to Minimize the Best Cost and Energy Consumption

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***Abstract*—Swarm intelligence is considered to be the discipline that pacts with natural as well as artificial systems poised of numerous individuals supposed to coordinate via decentralized control and self-organization. The discipline is supposed to emphasize the cooperative behavior resulting from the local interactions of the participating individuals among themselves and with the existing environment. These systems studied by swarm intelligence comprise colonies of termites and ants, flocks of birds, schools of fish, etc. The research conducted in the research paper concentrates on the performance of one of the most prominent swarm intelligence algorithm popularly known as PSO (Particle Swarm Intelligence). The swarms of neurons work collectively to achieve the best possible solution with the optimum use of available resources. The research paper elaborates a methodology described via an appropriate flowchart and algorithm intended to achieve the best cost under different scenarios with minimizing the energy consumption. Twelve different parameters have been considered to carry out the anticipated methodology via four different cases with alteration in the value of participating parameters. The obtained results have been described in both tabular and graphical forms.**

Keywords: Best Cost, Energy Consumed, Optimization, PSO, Swarm.

I. Introduction

Engineering problems have always been concerned with maximizing earns and minimizing losses. With the expansion of science and technology, the complexity concerned with optimization problems has also grown. The optimization approach is obligatory in engineering problems like mechanical design, logistics, nuclear reactors, and energy conservation and distribution [1], [2]. There are numeroustactics available via which one could maximize or minimize a function to find the optimal. Despite the availability of several optimization algorithms and techniques, none can be measured to be the best for different cases [3]. The best optimization technique for treatinga certain type of problem may not perform well for other types of problems. This depends on many features like whether the function is differentiable and its concavity (convex or concave) [4]. PSO (Particle Swarm Optimization) algorithm is capable of solving complex mathematical problems existing in engineering.PSO (Particle Swarm Optimization) is among the prominent metaheuristic algorithms inspired by swarm behavior similar to bird flocking and schooling in nature [5], [6]. PSO has found its applications in different sectors and is widely used. The working concept behind PSO is not too complicated. It is considered that a flying bird is at a certain position and has a certain velocity at any time. The bird changes its position by altering its velocity to search the food. The modification in velocity is reliant on its previous experience and the feedback received from the neighboring birds [7], [8]. The swarm of birds flying over a particular place needs to identify a point to the land which is a complex problem as finding such a point depends on several factors like maximizing the availability of the food and minimizing the risk of the existence of predators [9], [10]. The movement of the flock of birds takes place only when all the swarm members are willing to share information among themselves. In the absence of sharing information, each bird would land at a different point at a different time [11]. The birds of a swarm searching for the best point to land can know the best point until it is found by one of the swarm members [12], [13]. Every member of the swarm balances its individual and its swarm knowledge experience which is known as social knowledge [14]. This searching notion is artificially replicated for resolving non-linear optimization problems [15]. Each solution is reflected as a bird, called a particle. All the participating particles have a certain fitness value [16], [17]. The objective functions are used to evaluate these fitness values. The particles are supposed to preserve their specific best performance [18], [19]. They should also be aware of the best performance of their group [20]. The particles adjust their velocity bearing in mind their best performance and also considering the best performance of the best particle. The primary advantage of PSO over-optimization techniques is that it has fewer parameters to adjust. The flowchart depicting the working of PSO is shown in Fig. 1.

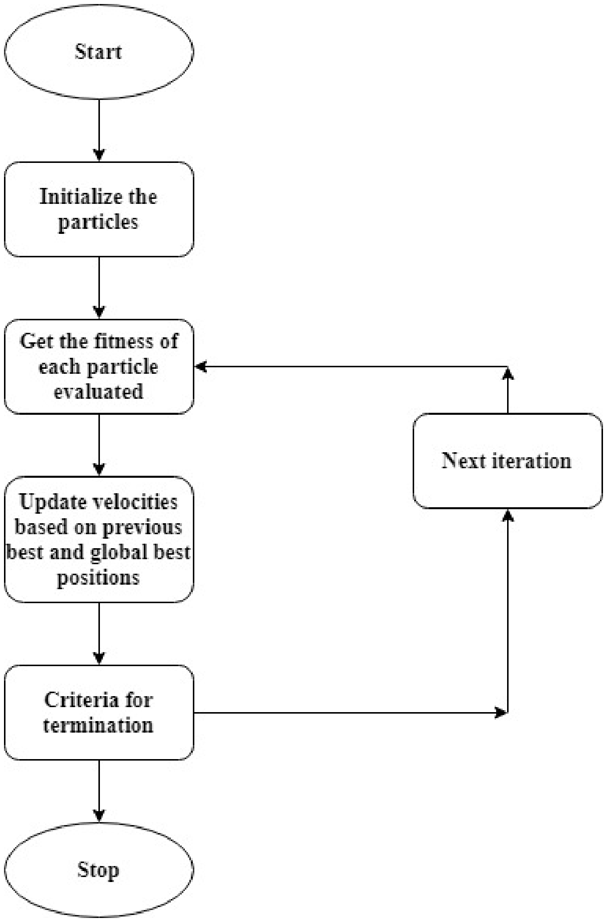

Fig. 1: Flowchart Depicting the Working of PSO

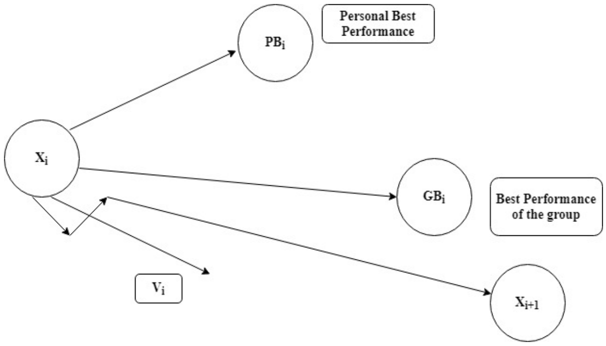

Fig. 2: Figure Depicts the Change Witnessed in Position Accompanied by a Change in Velocity

The equations for the updation of velocity and change in position are mentioned below as equation 1 and equation 2 respectively.

Equation for velocity update

$$V_{i+1} = \omega V_i + C_1 * \text{rand}(\,) * (PB_i - X_i) + C_2 * \text{rand}(\,) * (GB_i - X_i) \quad (1)$$

Equation for position update

$$Xi+1 = Xi + Vi+1 \quad (2)$$

C1 and C2 represents learning factors

ω represents inertia weight

ωV_i represents inertia effect

$C_1 * \text{rand}(\,) * (PB_i - X_i)$ represents local search and personal influence

$C_2 * \text{rand}(\,) * (GB_i - X_i)$ represents global search and social influence

Fig. 2 depicts the change in velocity and position caused by equations 1 and 2.

II. State of Art

In 2020, Naveen Bilandi, Harsh Kumar Verma, and Renu Dhir [21] elaborated the use of wireless body area networks for retrieving and communicating human health information utilizing sensors on the human body. The primary test for steering such activity is efficient energy management. This can be done by selecting the relay node for modeling the optimization problem. The authors compared three different nature-inspired metaheuristic algorithms for handling the relay node selection problem. The authors found that the total energy consumption using GWO (Grey Wolf Optimization) reduced by 23% when compared with PSO (Particle Swarm Optimization) and 16% when compared with ALO (Ant Lion Optimization). The authors concluded the supremacy of GWO as compared to the other two techniques because of its social hierarchy and hunting behavior. In 2020, Abdullah Khan, Hashim Hizam, Noor Izzribin Abdul Wahab, and Mohammad Lutfi Othman [22] proposed a metaheuristic algorithm HFPSO (Hybrid Firefly Particle Swarm Optimization) algorithm for solving different non-linear and convex OPF (optimal power flow) problems. HFPSO is a combination of FFO (FireFly Optimization) and PSO (Particle Swarm Optimization) algorithms intended to improve the exploitation tactics, investigation, and speed up the convergence rate. The authors focused on five objective functions concerned with OPF problems to justify the worth of the anticipated method. These functions are voltage profile improvement, total generation cost minimization, transmission lines active power loss reductions, voltage stability, and transmission lines reactive power loss reductions. The authors made use of MATLAB and tested the proposed method on a standard IEEE 30 busted system. The obtained results disclose that the anticipated method can produce an optimal and viable global solution with a high convergence rate. In 2020, Feng Qian, Mohammad Reza Mahmoudi, Hamid Parvin, Kim-Hung Pho, and Bui Anh Tuan [23] stated that traditional optimization algorithms fall short of handling naturally complicated optimization problems. Metaheuristic algorithms find themselves

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as a new kind of problem-solvers for finding solutions to these types of problems. The authors proposed an optimization algorithm accomplished in discovering the predictable quality of dissimilar locations and also tuning its exploration-exploitation impasse to the location of an individual. An innovative PSO (Particle Swarm Optimization) algorithm is presented to implement the conditioning learning behavior so that the particles are controlled to achieve a natural conditioning behavior on an unrestricted motive. Particles are classified into several categories. This is done so that the particles lying in a low diversity group would have the capability to travel to their best personal experience and the particles with high diversity would have the capability to move to the global optimal of that category. In the anticipated algorithm, the birds' natural conduct is employed to create an initial population arbitrarily or confusedly. Experiments delivered to associate the anticipated algorithm with the state-of-the-art methods demonstrate that the proposed optimization algorithm is one of the utmost effective and apposite ones to resolve the static optimization problems. In 2019, N. Bilandi, H.K. Verma, and R. Dhir [24] stated that WBAN (Wireless Body Area Networks) have a critical role to play in psychological and biomedical applications. The WBAN technology grieves from different utilization issues. The primary concern is energy consumption. Biosensors nodes regularly sense the signals and are supposed to send them to the sink which is an intensive energy consumption operation. The authors focused to come up with a routing mechanism making use of PSO (Particle Swarm Optimization) grounded on a metaheuristic algorithm with relay node selection via making use of distances and residual energies. The conducted research displays that the anticipated protocol proved to strike the perfect balance between curtailing the relay nodes and energy-efficient WBAN. In 2016, C. Vimalarani, R. Subramanian, and S. N. Sivanandam [25] emphasized on working of the WSN (Wireless Sensor Network) comprising several sensor nodes positioned to observe the physical entities in a target area. The examples include monitoring water level, temperature, pressure, military applications, and health care. Generally, sensor nodes perform enough operations and communication with the adjoining nodes via battery power. Energy conservation is important to maximize the lifetime of the WSNs. The authors made use of the PSO (Particle Swarm Optimization) algorithm and proposed a PSO algorithm based on clustering energy optimization to optimize the power consumption in WSN using the cluster head selection scheme. The authors evaluated different performance metrics and compared the results with the other clustering algorithms to validate the worth of the conducted research. The different performance metrics considered are network lifetime, packet delivery ratio, throughput, residual energy, normalized overhead, delay, and total energy consumed.

III. Research Methodology

This section elaborates the adopted methodology to conduct the research work intended to calculate the best cost and energy consumed in involved in the performance of PSO under different scenarios with changing the number of iterations and population size. The flowchart in Fig. 3 illustrates the adopted procedure to achieve the optimal results in terms of best cost and energy consumed followed by an algorithm defining the adopted steps for carrying out the research work.

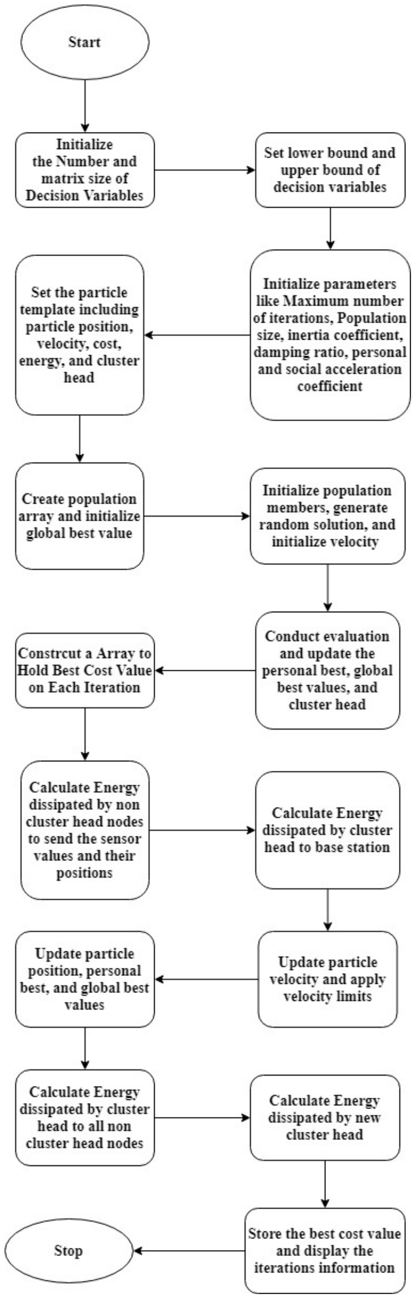

Fig.3: Figure Depicts the Flowchart Illustrating the Proposed Methodology for the Anticipated PSO Algorithm

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Algorithm
1. Initialize the Number of Decision variables and set the matrix size of Decision Variables.
2. Set lower bound and upper bound of decision variables.
3. Initialize parameters like the Maximum number of iterations, Population size, inertia coefficient, damping ratio, personal and social acceleration coefficient.
4. Set the particle template comprising particle position, velocity, cost, energy, and cluster head.
5. Generate population array and set global best value.
6. Initialize population members, generate a random solution, and initialize velocity.
7. Conduct evaluation and update the personal best, global best values, and cluster head.
8. Construct an array to hold the Best Cost Value on Each Iteration.
9. Calculate Energy dissipated by non-cluster head nodes to send the sensor values and their positions.
10. Calculate Energy dissipated by cluster head to the base station.
11. Update particle velocity and apply velocity limits.
12. Update particle position, personal best, and global best values.
13. Calculate Energy dissipated by cluster head to all non-cluster head nodes.
14. Calculate Energy dissipated by new cluster head.
15. Store the best cost value and display the iterations information.
16. End.

IV. Implementation and Results

This section presents the practical implementation of the proposed methodology considering four different cases having twelve parameters using MATLAB as a simulation tool. The results in each case are obtained in tabular as well as graphical format.

The research parameters used in the implementation of PSO are mentioned as under.

1. MaxIt - Refers to maximum number of iterations
2. nPop - Size of population
3. w - Inertia Coefficient
4. wdamp - Damping Ratio of Inertia Coefficient
5. c1 - Personal Acceleration Coefficient
6. c2 - Social Acceleration Coefficient
7. nVar - Number of Unknown (Decision) Variables
8. VarSize - Matrix Size of Decision Variables
9. VarMin - Lower Bound of Decision Variables
10. VarMax - Upper Bound of Decision Variables
11. MaxVelocity - 0.2* (VarMax-VarMin)
12. MinVelocity - - MaxVelocity

A. Case 1

The values assigned to the parameters are mentioned as under.

1. MaxIt - 10
2. nPop - 8
3. w - 1
4. wdamp - .99
5. c1 - 2
6. c2 - 2
7. nVar - 2
8. VarSize - [1 nVar]
9. VarMin - -10
10. VarMax - 10
11. MaxVelocity - 0.2* (VarMax-VarMin)
12. MinVelocity - - MaxVelocity

Table 1 shows the achieved Best Cost along with the Cluster Head for each iteration.The Best Cost calculated at iteration 1 (7.6115) is the Worst Cost as it is maximum. The Best Cost calculated at iteration 10 (4.0157) is the final Best Cost. For calculating the Average Cost, one needs to divide the sum of the calculated Best Cost at different iterations with the number of iterations. The calculated costs as per readings of Case 1 are mentioned as under.

Worst cost - 7.6115
Average cost - Sum of best cost at each iteration / Number of iterations
60.386 / 10= 6.0386
Best cost - 4.0157

Table 1: Table Displays the Achieved Best Cost Along with the Cluster Head for Case 1

Iteration	Best Cost	Cluster Head
1	7.6115	8
2	7.2645	3
3	7.1176	7
4	6.8092	8
5	6.5013	7
6	5.9816	4
7	5.4634	6
8	5.1162	8
9	4.505	3
10	4.0157	4

Fig. 4 depicts the readings obtained in Table 1 in graphical form. The blue rising line denotes the iteration

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number which ranges from 1 to 10 and is represented along the X-axis. The dipping orange line denotes the falling Best Cost against Y-axis from Iteration 1 (7.6115) to iteration 10 (4.0157). The grey line indicates the changing cluster heads with each iteration.

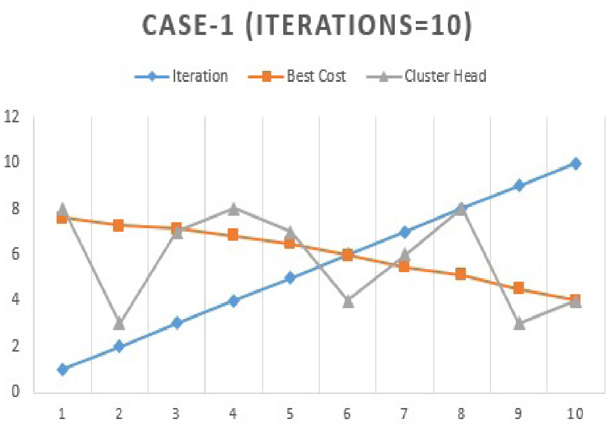

Fig. 4: Figure Depicts the Dipping Best Cost (orange line) from Iteration1 to Iteration 10 at Different Iterations (blue line) with Changing Cluster Heads (grey line) Readings Obtained in Table 1 in Graphical Form

Table 2 depicts the amount of energy consumed at different iterations. The maximum energy consumed is at iteration 1 (232.9261). The energy consumption gradually decreases from iteration 1 to iteration 10. The minimum energy consumed is at iteration 10 (142.0219). The average energy consumed is calculated by dividing the sum of energies consumed at each iteration by the number of iterations. The details of the energy consumed in this case are as follows.

Maximum energy	- 232.9261
Average energy	- Sum of energies consumed at each iteration/Number of iterations 1996.3751 / 10= 199.63751
Minimum energy	- 142.0219

Table 2: Table Depicts the Amount of Energy Consumed at Different Iterations

Iteration	Energy Consumed
1	232.9261
2	221.6715
3	221.6184
4	218.3917
5	210.9685
6	200.9526
7	200.5500
8	194.9542
9	152.3202
10	142.0219

Fig. 5 depicts the constructed graph as per readings of Case 1. The graph shows that the energy consumption decreased from 232.9261 at iteration1 to 142.0219 at iteration 10. The X-axis denotes the number of iterations and the Y-axis denotes the energy consumed.

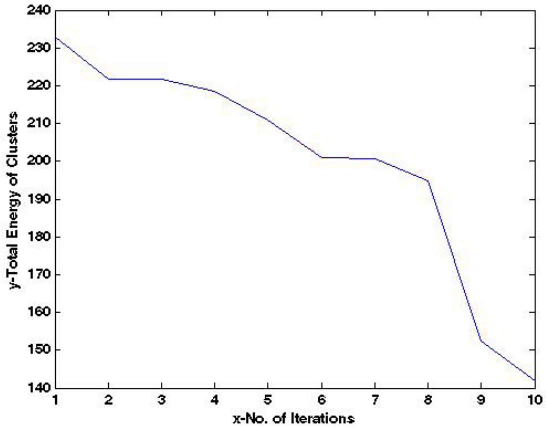

Fig. 5: Figure Depicts the Dipping Energy Consumption from Iteration1 to Iteration 10 at different Iterations

B. Case 2

The values assigned to the parameters are mentioned as under.

1. MaxIt - 25
2. nPop - 10
3. w - 1
4. wdamp - .99
5. c1 - 2
6. c2 - 2
7. nVar - 2
8. VarSize - [1 nVar]
9. VarMin - 10
10. VarMax - 10
11. MaxVelocity - 0.2* (VarMax-VarMin)
12. MinVelocity - MaxVelocity

Table 3 shows the achieved Best Cost along with the Cluster Head for each iteration. The Best Cost calculated at iteration 1 (10.8766) is the Worst Cost as it is maximum. The Best Cost calculated at iteration 25 (2.8454) is the final Best Cost. For calculating the Average Cost, one needs to divide the sum of the calculated Best Cost at different iterations with the number of iterations. The calculated costs as per readings of Case 2 are mentioned as under.

Worst cost	- 10.8766
Average cost	- Sum of best cost at each iteration / Number of iterations 129.9471 / 25 = 5.197884
Best cost	- 2.8454

Table 3: Table Shows the Best Cost Calculated at Each of 25 Iterations Along With the Cluster Head Node

Iteration	Best cost	Cluster Head
1	10.8766	10
2	10.0076	8
3	9.2405	9
4	8.4589	9
5	7.7139	8
6	6.8768	7
7	6.3323	3
8	5.1794	5
9	4.8955	6
10	4.8955	6
11	4.8955	6
12	4.3737	4
13	4.0944	1
14	4.0178	2
15	3.9877	10
16	3.8123	8
17	3.8123	8
18	3.8123	8
19	3.7181	7
20	3.7181	7
21	3.1723	9
22	3.1723	9
23	3.1723	9
24	2.8656	3
25	2.8454	1

Fig. 6 depicts the readings obtained in Table 3 in graphical form. The blue rising line denotes the iteration number which ranges from 1 to 25 and is represented along the X-axis. The dipping orange line denotes the falling Best Cost against Y-axis from Iteration 1 (10.8766) to iteration 25 (2.8454). The grey line indicates the changing cluster heads with each iteration.

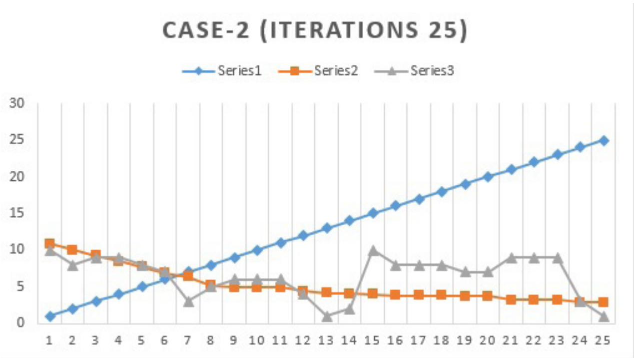

Fig. 6: Figure Depicts the Dipping Best Cost (orange line) from Iteration1 to Iteration 25 at Different Iterations (blue line) with Changing Cluster Heads (grey line) Readings Obtained In Table 3 in Graphical Form

Table 4 depicts the amount of energy consumed at different iterations. The maximum energy consumed is at iteration 1 (257.0583). The energy consumption gradually decreases from iteration 1 to iteration 25. The minimum energy consumed is at iteration 25 (122.6915). The average energy consumed is calculated by dividing the sum of energies consumed at each iteration by the number of iterations. The details of the energy consumed in this case are as follows.

Maximum energy - 257.0583

Average energy - Sum of energies consumed at each iteration/Number of iterations

4807.463 / 25= 192.29852

Minimum energy - 122.6915

Table 4. Table shows the Readings of Energy Consumed at Different Iterations

Iteration Number	Energy consumed in Joules
1	257.0583
2	250.5302
3	239.9339
4	238.9549
5	237.4106
6	236.2411
7	235.7080
8	235.3742
9	234.0775
10	233.2034
11	229.6987
12	228.9613
13	228.7728
14	228.1980
15	220.0203
16	141.2064
17	130.0063
18	128.7128
19	126.9582
20	126.8394
21	125.1047
22	124.8543
23	124.2314
24	122.7151
25	122.6915

The graphical representation of energy consumed (Y-axis) against the number of iterations (X-axis) is shown in Fig. 7. Fig. 7 depicts the constructed graph as per readings of Case 2. The graph shows that the energy consumption decreased from 257.0583 at iteration1 to 122.6915 at iteration 25. The X-axis denotes the number of iterations and the Y-axis denotes the energy consumed.

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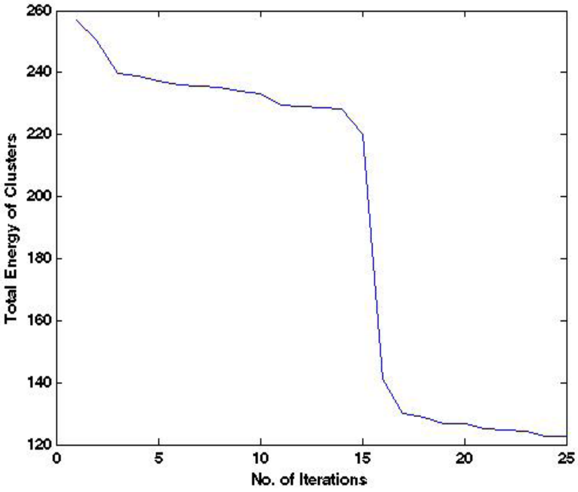

Fig. 7: Figure Depicts the Dipping Energy Consumption from Iteration1 to Iteration 25 at Different Iterations

C. Case 3

The values assigned to the parameters are mentioned as under.

1. MaxIt - 50
2. nPop - 10
3. w - 1
4. wdamp - .99
5. c1 - 2
6. c2 - 2
7. nVar - 2
8. VarSize - [1 nVar]
9. VarMin - -10
10. VarMax - 10
11. MaxVelocity - 0.2* (VarMax-VarMin)
12. MinVelocity - MaxVelocity

Table 5 shows the achieved Best Cost along with the Cluster Head for each iteration. The Best Cost calculated at iteration 1 (10.0621) is the Worst Cost as it is maximum. The Best Cost calculated at iteration 50 (0.75908) is the final Best Cost. For calculating the Average Cost, one needs to divide the sum of the calculated Best Cost at different iterations with the number of iterations. The calculated costs as per readings of Case 3 are mentioned as under.

Worst cost - 10.0621
Average cost - Sum of best cost at each iteration / Number of iterations
164.45456 / 50 = 3.2890912
Best cost - 0.75908

Fig. 8 depicts the readings obtained in Table 5 in graphical form. The blue rising line denotes the iteration number which ranges from 1 to 50 and is represented along the X-axis. The dipping orange line denotes the falling Best Cost against Y-axis from Iteration 1 (10.0621) to iteration 50 (0.75908). The grey line indicates the changing cluster heads with each iteration.

Table 5: Table shows the Best Cost Calculated at each of 50 Iterations Along with the Cluster Head Node

Itera-tions	Best Cost	Cluster Head	Itera-tions	Best Cost	Cluster Head
1	10.0621	10	26	2.6041	8
2	9.1113	9	27	2.3768	6
3	8.8284	1	28	2.2853	2
4	8.6458	5	29	2.2853	2
5	8.1514	4	30	2.2853	2
6	7.0856	7	31	1.7066	10
7	5.9408	8	32	1.6333	7
8	5.0671	3	33	1.6333	7
9	5.0671	3	34	1.6333	7
10	5.009	6	35	1.6333	7
11	4.6749	10	36	1.6333	7
12	4.5388	2	37	1.6333	7
13	4.4468	1	38	1.6333	7
14	4.4468	1	39	1.5752	6
15	3.8129	9	40	1.4322	3
16	3.8129	9	41	1.4322	3
17	3.8129	9	42	1.4322	3
18	3.8129	9	43	1.4216	4
19	3.4091	4	44	0.75908	10
20	3.4091	4	45	0.75908	10
21	2.8503	5	46	0.75908	10
22	2.8503	5	47	0.75908	10
23	2.8166	7	48	0.75908	10
24	2.6041	8	49	0.75908	10
25	2.6041	8	50	0.75908	10
26	2.6041	8			

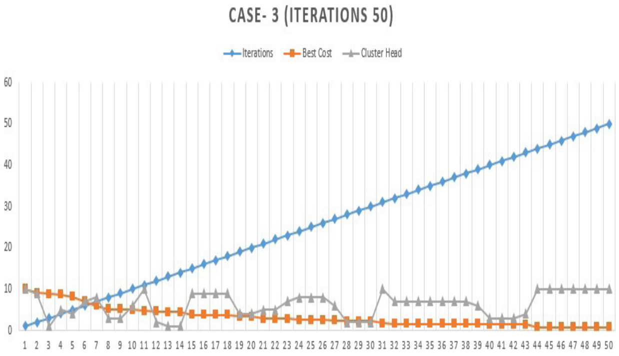

Fig. 8: Figure Depicts the Dipping Best Cost (orange line) from Iteration1 to Iteration 50 at Different Iterations (blue line) with Changing Cluster Heads (grey line) Readings Obtained in Table 5 in Graphical Form

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Table 6 depicts the amount of energy consumed at different iterations. The maximum energy consumed is at iteration 1 (274.937). The energy consumption gradually decreases from iteration 1 to iteration 50. The minimum energy consumed is at iteration 50 (0). The average energy consumed is calculated by dividing the sum of energies consumed at each iteration by the number of iterations. The details of the energy consumed in this case are as follows.

Maximum energy	-	274.937
Average energy	-	Sum of energies consumed at each iteration/Number of iterations 5442.8967 / 50= 108.857934
Minimum energy	-	0

Table 6. Table Shows the Readings of Energy Consumed At Different Iterations

Iterations	Energy Consumed	Iterations	Energy Consumed
1	274.937	26	114.4045
2	263.6115	27	113.939
3	263.2299	28	113.6311
4	261.9676	29	113.0824
5	258.7445	30	113.0471
6	255.2696	31	110.7386
7	249.4896	32	32.1854
8	246.96	33	21.3523
9	246.5421	34	21.1707
10	246.2428	35	20.4617
11	237.9748	36	20.1175
12	138.6769	37	19.7634
13	125.5546	38	19.0432
14	124.1483	39	18.9522
15	123.2218	40	18.6826
16	122.785	41	18.1531
17	119.5621	42	17.849
18	117.4677	43	17.7305
19	117.4647	44	16.6961
20	117.3091	45	10
21	116.8824	46	0
22	116.8678	47	0
23	115.8194	48	0
24	115.8035	49	0
25	115.3636	50	0

The graphical representation of energy consumed (Y-axis) against the number of iterations (X-axis) is shown in Fig. 9. Fig. 9 depicts the constructed graph as per readings of Case 3. The graph shows that the energy consumption decreased from 274.937 at iteration1 to 0 at iteration 50. The X-axis denotes the number of iterations and the Y-axis denotes the energy consumed.

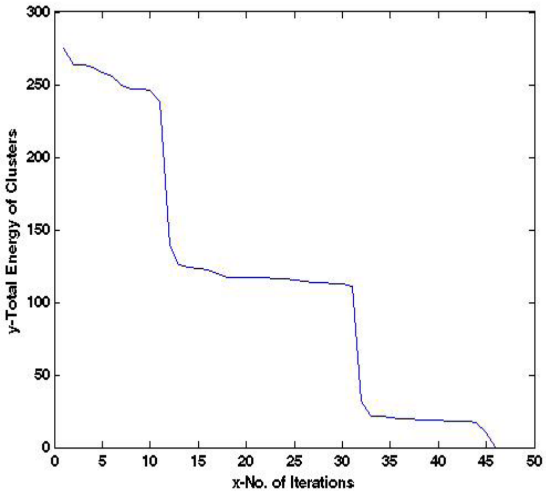

Fig. 9: Figure Depicts the Dipping Energy Consumption from Iteration1 to Iteration 50 at Different Iterations

D. Case 4

The values assigned to the parameters are mentioned as under.

1. MaxIt - 100
2. nPop - 10
3. w - 1
4. wdamp - .99
5. c1 - 2
6. c2 - 2
7. nVar - 2
8. VarSize - [1 nVar]
9. VarMin - 10
10. VarMax - 10
11. MaxVelocity - 0.2* (VarMax-VarMin)
12. MinVelocity - MinVelocity

Table 7 shows the achieved Best Cost along with the Cluster Head for each iteration. The Best Cost calculated at iteration 1 (10.9913) is the Worst Cost as it is maximum. The Best Cost calculated at iteration 37 (0.83969) and remains static till the 100th iteration with the same Cluster Head (4). For calculating the Average Cost, one needs to divide the sum of the calculated Best Cost at different iterations with the number of iterations. The calculated costs as per readings of Case 4 are mentioned as under.

Worst cost	-	10.0621
Average cost	-	Sum of best cost at each iteration / Number of iterations 205.64676 / 100 = 2.0564676
Best cost	-	0.83969

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Table 7: Table shows the Best Cost Calculated at each of 100 Iterations along with the Cluster Head Node

Itera-tions	Best Cost	Cluster Head	Itera-tions	Best Cost	Cluster Head
1	10.9913	7	51	0.83969	4
2	10.042	8	52	0.83969	4
3	8.8534	9	53	0.83969	4
4	8.1575	4	54	0.83969	4
5	7.0097	10	55	0.83969	4
6	6.3151	6	56	0.83969	4
7	5.5613	1	57	0.83969	4
8	4.9034	5	58	0.83969	4
9	4.7716	4	59	0.83969	4
10	4.6426	2	60	0.83969	4
11	4.6426	2	61	0.83969	4
12	4.6426	2	62	0.83969	4
13	4.6426	2	63	0.83969	4
14	4.5701	3	64	0.83969	4
15	4.4119	8	65	0.83969	4
16	4.4119	8	66	0.83969	4
17	3.9624	9	67	0.83969	4
18	3.9624	9	68	0.83969	4
19	3.9624	9	69	0.83969	4
20	3.6113	7	70	0.83969	4
21	3.4693	6	71	0.83969	4
22	3.3045	10	72	0.83969	4
23	3.3045	10	73	0.83969	4
24	3.0453	1	74	0.83969	4
25	3.0453	1	75	0.83969	4
26	3.0453	1	76	0.83969	4
27	2.3544	3	77	0.83969	4
28	2.3544	3	78	0.83969	4
29	2.2938	4	79	0.83969	4
30	1.8809	5	80	0.83969	4
31	1.817	7	81	0.83969	4
32	1.817	7	82	0.83969	4
33	1.8051	5	83	0.83969	4
34	1.7131	6	84	0.83969	4
35	1.2943	8	85	0.83969	4
36	1.2943	8	86	0.83969	4
37	0.83969	4	87	0.83969	4
38	0.83969	4	88	0.83969	4
39	0.83969	4	89	0.83969	4
40	0.83969	4	90	0.83969	4
41	0.83969	4	91	0.83969	4
42	0.83969	4	92	0.83969	4
43	0.83969	4	93	0.83969	4
44	0.83969	4	94	0.83969	4
45	0.83969	4	95	0.83969	4
46	0.83969	4	96	0.83969	4
47	0.83969	4	97	0.83969	4
48	0.83969	4	98	0.83969	4
49	0.83969	4	99	0.83969	4
50	0.83969	4	100	0.83969	4

Fig. 10 depicts the readings obtained in Table 7 in graphical form. The blue rising line denotes the iteration number which ranges from 1 to 100 and is represented along the X-axis. The dipping orange line denotes the falling Best Cost against Y-axis from Iteration 1 (10.9913) to iteration 100 (0.83969). The grey line indicates the changing cluster heads with each iteration.

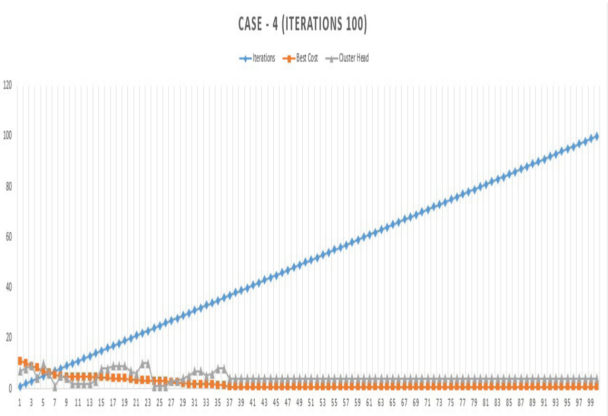

Fig. 10: Figure Depicts the Dipping Best Cost (orange line) from Iteration1 to Iteration 100 at Different Iterations (blue line) with Changing Cluster heads (grey line) Readings Obtained in Table 7 in Graphical Form

Table 8 depicts the amount of energy consumed at different iterations. The maximum energy consumed is at iteration 1 (273.8961). The energy consumption gradually decreases from iteration 1 to iteration 100. The minimum energy consumed is at iteration 100 (0). The average energy consumed is calculated by dividing the sum of energies consumed at each iteration by the number of iterations. The details of the energy consumed in this case are as follows.

Maximum energy - 273.8961

Average energy - Sum of energies consumed at each iteration/Number of iterations

4787.9178 / 100= 47.879178

Minimum energy - 0

Table 8: Table Shows the Readings of Energy Consumed at Different Iterations

Iterations	Energy Consumed	Iterations	Energy Consumed
1	273.8961	51	0
2	261.1575	52	0
3	258.6126	53	0
4	257.545	54	0
5	250.3606	55	0
6	220.6782	56	0
7	210.0794	57	0
8	207.9891	58	0
9	204.7667	59	0
10	203.8721	60	0
11	202.6316	61	0
12	200.4358	62	0
13	198.9953	63	0
14	197.3228	64	0
15	195.3197	65	0
16	194.1674	66	0
17	192.3881	67	0
18	192.2679	68	0
19	190.6705	69	0
20	190.2147	70	0
21	189.5654	71	0
22	181.8752	72	0
23	103.1061	73	0
24	10	74	0
25	0	75	0
26	0	76	0
27	0	77	0
28	0	78	0
29	0	79	0
30	0	80	0
31	0	81	0
32	0	82	0
33	0	83	0
34	0	84	0
35	0	85	0
36	0	86	0
37	0	87	0
38	0	88	0
39	0	89	0
40	0	90	0
41	0	91	0
42	0	92	0
43	0	93	0
44	0	94	0
45	0	95	0
46	0	96	0
47	0	97	0
48	0	98	0
49	0	99	0
50	0	100	0

The graphical representation of energy consumed (Y-axis) against the number of iterations (X-axis) is shown in Fig. 11. Fig. 11 depicts the constructed graph as per readings of Case 4. The graph shows that the energy consumption decreased from 273.8961 at iteration1 to 0 at iteration 100. The X-axis denotes the number of iterations and the Y-axis denotes the energy consumed.

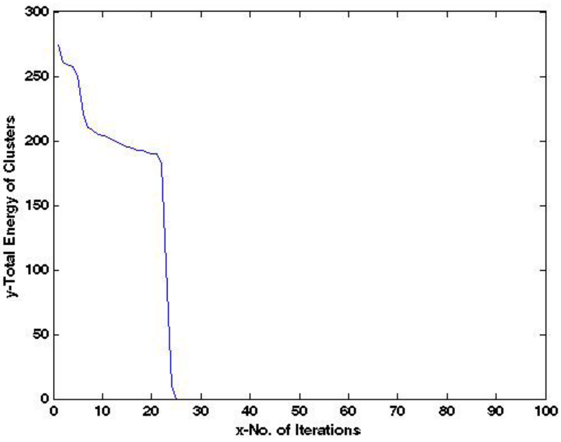

Fig. 11: Figure Depicts the Dipping Energy Consumption from Iteration1 to Iteration 50 at Different Iterations

V. Conclusion

The research conducted in the research paper showed that the readings of best cost and energy consumed continuously decreased with the passing iteration. The graphs plotting best cost against several iterations have witnessed a continuous downfall. Similarly, the graphs concerning energy consumption have also witnessed a downfall in the consumption of energy with the passing iterations. The witnessed downfall in both cases is appreciable and proves the worth of the conducted research. In case 3 the energy consumed reached 0 at the 46th iteration and in case 4 the energy consumed reached 0 at the 25th iteration. So it can be concluded that in instances with a larger number of iterations, the energy consumption can reduce to 0 midway. The

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best cost in all the implemented cases has witnessed a continuous downfall which is again a good sign. So, it can be concluded that the anticipated research work using the working principle of PSO has achieved better results. In the future, the number of parameters can be further increased, the values of constants can be altered and even cases with a larger number of iterations can be considered with focus to achieve optimum results. The research can be further extended to other swarm intelligence algorithms and compared with the research work conducted in this research paper.

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