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NODE REPLACEMENT BASED ENERGY OPTIMIZATION USING ENHANCED SALP SWARM ALGORITHM (ES2A) IN WIRELESS SENSOR NETWORKS

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Abstract

The use of wireless sensor networks (WSN) is essential in many applications. To offer innovative capabilities and solutions, WSN presents novel methods. In terms of energy autonomy, the limited resources of the sensor node are a real constraint. While considering other conflicting terms like less secure routing and energy consumption, its goal is to improve network lifetime and avoid node failure to reduce data transmission delays. The Optimization formulation is presented to select CH to increase network lifetime and reduce energy consumption to solve routing issues. An effective optimization method offers the best solution. A major factor is a connectivity, if connectivity may lose because of a node failure, which creates network disruption by generating energy losses or network fails. In this paper, the Enhanced Salp Swarm Algorithm (ES2A) is proposed to optimize the network by replacing it to find the faulty one and then replacing it with its neighbouring node to transfer the data packets. This work guarantees the reduced energy consumption of the nodes, which guarantees the network's maximum lifetime. As nodes are reduced, energy consumption is also reduced accordingly. The experimental result is carried out on the NS2 platform. The performance metrics of the ES2A were enhanced when compared to the existing schemes, which are as follows, the lifetime of the network reaches 85.69%, the energy consumption is 15.87%, and the loss of packets in the network is 12%, throughput is 79.9%, and the delivery ratio of packets reaches 98.02%.

Keywords: Communication, Energy consumption, Enhanced salp swarm algorithm, Node replacement, Optimization.

1. Introduction

WSN consist of tiny devices called sensors that transmit/receive the information in an ad hoc wireless configuration. Within the physical environment, the nodes are deployed randomly. It measures the physical parameters of the environment and forwards the information to the outside world. The recent advances in computation, communication and detection methods are coupled together to monitor the physical phenomenon for the development of WSN [1].

WSN is most popular in commercial/industrial applications, owing to its advancements in computation, communication, and the use of low-power integrated elements. For monitoring the environment's conditions such as pressure, sound, position, temperature, humidity, vibration, etc., sensor nodes (SN) are used. SN performs various tasks such as localization, synchronization, sensing, processing, the discovery of targets, routing, aggregation, and target tracking in many real-time applications [2].A cluster is the group of sensors to obtain the data that is aggregated locally.

To reduce the bandwidth utilization, any group node that aggregates the data is called Cluster Head (CH) and used to analyse local data, which reduces the data redundancy. While clustering, the nodes are divided into numerous sets called clusters. The CH is used to gather the data received from all its members and send it to BS [3].

To design the energy balancing routing protocol, the optimal selection of CH is a major problem. Many platforms of sensor networks operate under batteries that prominent in many energy constraints. One among them is limited energy in WSNs, which is unsuitable for several applications. Hence, nodes cannot work efficiently, which is the main drawback of WSN. Moreover, replacing or charging energy resources is impossible. The optimization technique develops the algorithms, mathematical ideas, and tools used to find optimal values for the given problem by considered some constraints [4]. Figure 1 shows the structure of the WSN architecture. This paper's major objective is to prolong the lifetime of WSNs by selecting the optimum number of clusters.

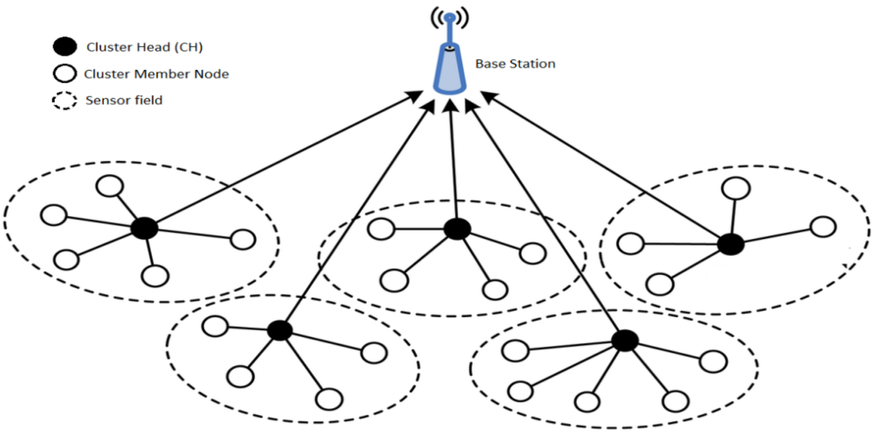

Fig. 1. WSN architecture.

To ensure a uniform load on every cluster and manage the smooth power dissipation by each node, ES^2A is introduced. To transmit the data efficiently, the node is replaced by the neighbouring node in case of any damage at that time. Recently most of the research focused on optimization in WSN. An effective optimization technique offers an optimal solution. This method is used to exchange data with its patterns and its results. Recent bio-inspired optimization research activities are carried out from different types of nature and their objectives. For data communication in WSN, energy consumption is the main factor that can be reduced by reducing traffic during communication. Most of the researcher's attention is on the network's performance, like detection coverage and network connectivity [5].

A new approach is proposed to optimize the node that analyses the network's energy consumption to overcome those issues. As a result, the main objective of WSN is to enhance network lifetime and robustness [6].The rest of this paper is presented as Works related to the proposed method are given in Section 2. The research objectives and methodology in Section 3 show the results and discussion in Section 4, concluding the proposed work with the future direction in Section 5.

2. Literature Survey

This section provides the related studies carried out previously, the network that uses the best methods for energy consumption to provide the best optimization results. Selvaraj and Rathipriy [7] discussed the optimization methods of WSN. WSN contains many SNs where each node collects data from the application environment and transfers it to BS. Optimization methods are used to reduce power consumption to solve routine problems. Numerous optimization methods are proposed to improve energy consumption and network lifetime. To solve energy-based lifespan optimization, this research provides an overview of successful SI techniques classes.

Sharma and Sharma [8] battery power of the SN is restricted in general, and it is not easy to replace over the large geographic areas. Therefore, many protocols are proposed to conserve energy, but many improvements can still be made. To triumph over the limitations of the previous work, an improved method was suggested. This method defeated the difficulties faced in tree routing protocol using reactivity and optimized route selection based on cuckoo search optimization. MATLAB is used to calculate the efficiency of the proposed protocol. The simulated outcomes proved that this method outperformed compared GSTEB in terms of residual energy and lifetime of networks.

Cheng and Xia [9] suggested the effective cuckoo search (CS) for node localization. To construct the mutation probability for avoiding the local optimum, each solution's fitness function is used. To approach the optimal global solution, this method enables the population. This method restricts the population to avoid energy consumption caused by irrelevant searching. Concerning the localization success ratio and the average localization error, to study the effects of specifications such as the density of sensors, the boundary of communication, and total anchor nodes in the proposed technique, extensive experiments are performed. In addition to performing the same localization using the same network implementation, a comparative study was conducted. The experiment results show that this technique does not improve the convergence rate but reduces the average localization compared to the PSO and CS technique.

Wang et al. [10] presented a comprehensive solution for addressing the issues related to node failure. The single node failure problem with cooperative communication was solved using the CSFR approach, whose enhanced version CSFR-M effectively handled the failure of a single node problem and the node movement. CCRA was presented based on the nodes' manoeuvrability and cooperative communication to restore network connectivity after numerous nodes' failure. After detecting node failure, restoration of connectivity was initiated by reactive methods such as CCRA and CSFR-M. The CCRA simplifies the network restoration process to reduce energy dissipation further. By choosing the nearest neighbour, the distance between the individual nodes is minimized for travel recovery. The performance of CSFR-M, CCRA and CSFR is validated by extensive simulations. To extend the life of the network, energy-efficient routing algorithms are developed. To efficiently exploit the energy of the network, the clustering concept is widely used. It is noted that the formation of clustering is an NP-hard issue in the literature.

Demriet al. [11] proposed the Enhanced Cuckoo Search (ECSBCP) based search for WSN routing. For this purpose, many meta-heuristic methods are presented. An improvement was made on multi-objective CH based on various metrics, such as distance and energy. The experimental results show that the number of dead nodes, the network's output, the extension of the network lifetime and the time interval confirmed that this method performs well than LEACH. Future work is intended to implement the multi-hop fashion of the proposed protocol to optimize CH energy use. Search for a new optimization using nature and adapt them to the WSN field.

The precise location of SN has a strong influence on the efficiency of WSN. Arora and Singh [12] presented the butterfly optimization technique for localizing nodes. This method uses the application of the meta-heuristic technique inspired by nature. The proposed method is evaluated using Gaussian noise in various sensor networks where the range of nodes was from 25 to 150, and distance values were corrupted. To ensure the proposed one's efficiency, it is compared with some existing FA and PSO methods. The simulated outcomes show that this proposed method provides an accurate and more consistent node location than the PSO and FA methods.

Wang et al. [13] proposed the improved grey wolf optimization technique (IGWO) to improve the slow convergence deficiencies, easy to fall into the local optima, as well as low search precision. To balance the relationship between local and GS, a nonlinear convergence factor was designed. To prevent from being destroyed as an iteration behaviour, an elite method was proposed. The main wolves guide the remaining wolves to hunt reasonably so that the original weighting method is improved. Designing the grey wolf boundary position method and introducing the dynamic variation method enriches the population's diversity and improves the proficiency of the methods to jump local optima. To validate GA's convergence performance, Gray Wolf Optimizer, IGWO and PSO, the standard function is used, which shows that this proposed method has a better performance compared to other techniques. The IGWO technique is incorporated to implement with WSNs. The simulation results indicate that, compared to GWO, the IGWO technique has improved WSN nodes' coverage and produces a huge coverage rate with fewer nodes, in addition to minimizing network deployment cost.

Coverage is as emerging and fundamental research topic for all kinds of applications in WSN. To obtain valid data and monitor the field of interest, Wang et al. [14] proposed the improved WA coverage optimization for WSNs. To obtain full coverage for the area of interest, a mathematical model was proposed. To optimize the population's initial distribution, the idea of reverse learning was presented in the original WSOA method. This technique improves node search capabilities and speeds up GS. The experiment results show that this method improves node coverage in WSN and optimizes network performance.

Tchuani et al. [15] suggested a greedy algorithm that prioritizes sensors with the lowest energy and then used the blacklist that maximizes the number of nodes that cover intended targets. The proposed algorithm outperformed the previously published schemes. To develop the regular arrays, an analytical strategy that shows the optimal solution, all the sensors' energy becomes zero. The theoretical approach clarifies that the modern light shows in the connected ring of odd-sized sets, which is tricky rather than considering the non-disjoint cover sets. Rani et al. [16] proposed a hybrid method which is a combination of two algorithms such as Genetic Algorithm (GA) and Bacterial Search Optimization (BFO). It is applied along with the destination sequence distance vector (DSDV) routing protocol individually. The metrics used for the validation are end-to-end delay, bit error rate, throughput, delivery of packets, routing overhead, and congestion. The experimental results show that DSDV routing protocol's hybrid method provides better performance than existing schemes and shows suitable for small network size.

3. Research Methodology

This research's main focus is to improve the network's lifetime and avoid node failure to reduce the delay while considering other conflicting measures, such as reduced energy consumption and efficient routing. The optimization formulation was a novel one that chooses CH to increase network lifetime. Transmission range of SN affects battery depletion and the network's lifetime. It also aims to evaluate the coordinates of unknown nodes with the help of known nodes. Congestion can cause a large amount of spent energy for each node, leading to an extreme amount of data collecting and processing. Therefore, the main drawback is balancing the power between the nodes. To overcome this limitation, an enhanced Salp Swarm Algorithm (ES2A) is proposed for node replacement and simultaneously balances the energy utilization between nodes and optimizes the network to transfer data efficiently, as shown in Fig. 2.

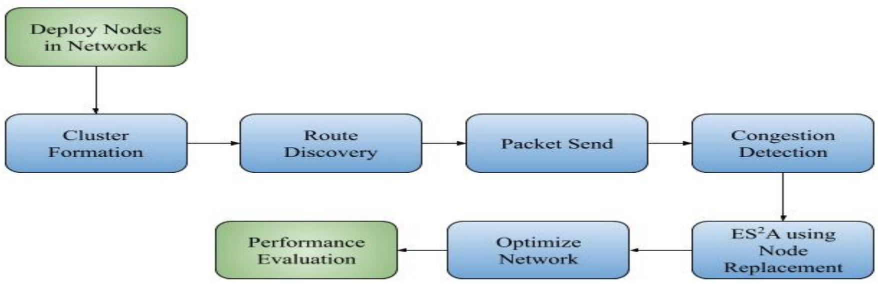

Fig. 2. Flow of proposed research work.

Congestion detection: The most common detection parameters are transmission delay, channel load, packet loss and queue length. This proposed method is used for reliable detection, and it replaces the node that is congested by the heavy load on the node that can no longer transfer the data.

Enhanced Salp Swarm Algorithm (ES²A) - This method is used to optimize the network lifetime. If any node is damaged and unable to transmit the data, get coordinate with neighbour nodes to replace that damaged node. This paper presents an enhanced SSA version, which increases existing SSA performance by utilizing node replacement called Enhanced SSA (ES²A). Biological research on Salps and their living environments are difficult to access. It is also very difficult to maintain them in a limited boundary, which is the main motivation for developing the Salp swarm technique [17]. Salps have swarmed in the deep oceans known as the Salp chain, which helped obtain better locomotion while foraging.

The mathematical model for ES²A is given in Eq. (1)

$$S_j^i = \begin{cases} FS_j + r_1\left[(ub_j - lb_j)r_2 + lb_j\right] r_3 \geq 0 \\ FS_j - r_1\left[(ub_j - lb_j)r_2 + lb_j\right] r_3 < 0 \end{cases} \tag{1}$$

where, S_j^i is the First salps (cluster head) position in *j^th^* dimension, FS_j is Food Source's position in j^{th} dimension, ub_j is upper bound in j^{th} dimension, lb_j is lower bound in j^{th} dimension and r_2, r_3 is random numbers based on the interval [0,1].

The most important parameter is the significant coefficient r_1 which is used to balance the searching and utilization of food as in Eq. (2):

$$r_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{2}$$

where r_1 is a significant coefficient of ES²A, the current round is indicated by 1, L represents the maximum number of rounds.

A very important measure in WSN is that sensor monitoring fails in the area. The sensor's application requires that the distance between the measured data exceeds a particular period (for example, 30 s). Consider that the sensor is 50m away from any faulty sensor node, then it takes a minute to travel to calculate the distance, then it does not meet the application requirements. Also, the sensor travels at this distance, causing a large amount of energy consumption; this leads to sensor failure. Therefore, the failure node's energy is shared with other neighbouring nodes that seem like a reasonable solution.

Fitness function for routing*:* This is used for measuring the quality of the solution about the metrics involved. Moreover, at every iteration, alpha, beta and delta solutions are updated. Novel fitness function is constructed to generate an efficient and reliable routing path from every gateway to BS. Overall Distance (OD) covered by gateways is given by the Eq. (3)

$$OD = \sum_{i=1}^{n} dist(g_i, NextG(g_i)) \tag{3}$$

The total hops are given in Eq. (4).

$$GH = \sum_{i=1}^{n} NextGCount(g_i) \tag{4}$$

By taking the minimum distance covered and minimum hop count, routing is performed. Hence, for smaller distances and hops, the fitness value for the solution is higher. The solution which produced the highest fitness value is said to be the best solution. The fitness function which was constructed is described in Eq. (5).

$$Routing\ Fitness = C/(w1 * OD + w2 * GH) \tag{5}$$

where $(w1,w2)\ \epsilon[0,1]$ such that, $w1 + w2 = 1$ and C is a proportionality constant.

The fitness function provides a balance between the overall distance and total hops in the network.

Fitness function evaluation: While receiving information from SNs of the respective clusters, aggregating them and then transmitting back directly to BS or other gateways, gateways require energy. The energy consumed in one round by the gateway g_i associated with SNs n_i is formulated in Eq. (6) to perform various cluster operations.

$$E_{Cluster}\,(g_i) = n_i * E_{rec} + n_i * E_{DA} + E_{tran}(g_i, NextG(g_i)) \tag{6}$$

where $Erec$, E_{DA}, and E_{tran} are the energy consumed while receiving, aggregating, and transmitting data to the other gateway. Conversely, any random gateway g_i even consumes energy for receiving and forwarding the data among gateways which is recursively formulated, as given in Eqs. (7) and (8).

$$Data_{incoming}\,(g_i) = \begin{cases} 0 & if\ NextG(g_i) \neq g_i \forall g_j \in GH \\ \sum\{Data_{incoming}(g_j) | NextG(g_i) = g_i, g_j \in GH\} & Else \end{cases} \tag{7}$$

$$E_{forw}(g_i) = Data_{incoming}(g_i) \times E_{tran}\big(g_i, NextG(g_i)\big) + Data_{incoming}(g_i) \times E_{rec} \tag{8}$$

The gateway's total energy is the sum of energy consumed to perform all operations in the cluster and forward the received data from other gateways and Eq. (9).

$$E_{gateway}(g_i) = E_{cluster}(g_i) + E_{forw}(g_i) \tag{9}$$

Node Replacement (NR): The neighbouring nodes' distances are calculated to replace the damage or the defective node in the network. When calculating the node's distance to replace the faulty or busy node, Eq. (10) is utilized.

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{10}$$

where (x, y) are the target node coordinates, d_i is the distance between target nodes

$$f(x, y) = \min\,(\textstyle\sum_{i=1}^{M}(\sqrt{(x - x_i)^2 + (y - y_i)^2})^2) \tag{11}$$

where *'i'* is an intermediate node within particular target nodes transmission range.

Position of salps followers of ES^2 algorithm, which is updated by the equation based on Newton's law of motion:

$$S_j^i = \frac{V_{final}t^2}{2V_0} + V_0 t \tag{12}$$

where $V_0$is initial velocity, t is time, V_{final} is final velocity obtained, $i \geq 2$ then, the S_j^i represents the i^{th} node position of j^{th} dimension.

ES²A-NR Algorithm

1: **BEGIN**
2: Initialize the number of Node, Max rounds
3: **while** Max rounds do
4: **for** each node, do
    If (node failed detected), **then**
        Elected = false;
      Elseif (node=clusterhead) **then**
        Elected = true;
      end if
    end if
  end for
5: D is the Destination (best)
6: **Update**'r1'
7: **for** each node, do
8: **if** i = =1then
      Update position of the neighbour node
   else
      Update position of next node
      t=t+1
  endif
9: **end for**
10: **end while**
11: **return** 'D' as the best solution
12: **END**

4. Results and Discussion

The open-source simulating tool NS2 is used for implementing and validating the proposed optimization algorithm. The 1000 nodes are also randomly distributed in 100m * 100m square area (i.e. size of the network). Table 1 shows the simulation parameter descriptions below:

Table 1. Simulation parameters.

Parameters	Description
Number of Nodes	1000
Network Size	100 m×100 m
Packet size	512 bytes
Node transmission range	20 meters
Initial Energy	2 joules

Performance analysis of the existing and proposed methods is carried out in terms of a given network's lifetime, delivery of packets, packets loss, and throughput. The performance of ES^2A is compared with different well-known optimization algorithm like

- Enhanced Grey wolf optimizer (EGWO)
- Improved Particle swarm optimization (IPSO)
- Enhanced Butterfly optimization algorithm (EBOA)

Improved Particle Swarm Optimization (IPSO): The objective of the MPSO is to expand the range of the best positions that each particle and swarm can hold to improve PSO performance [18]. The MPSO is proposed, which can be worked to solve some standard problems, and then it can be combined with other metaheuristic algorithms to solve common nonlinear optimization problems. Enhanced Butterfly Optimization Algorithm (EBOA) [19]: An Enhanced Butterfly Optimization Algorithm (EBOA) can be constructed by incorporating the original BOA with the Cross-Entropy (CE) method. With the co-evolution approach, a novel method is achieved to balance investigation and utilization to improve its global searchability and efficiently ignore the local optima issue.

A 19 test functions used for evaluation, the new method's performance performs better in terms of optimal local exploitation, exploration, convergence rate, and avoidance. The simulated outcomes of the given test function verify that the proposed algorithm efficiently ignores the local optima's value and then has outstanding local and global search capabilities. Due to the co-evolutionary technique, the new method can find a proper balance between investigation and usage. It has superior performance to solve the optimization function's difficult problems. Enhanced Gray Wolf Optimization (EGWO) [20]: In the original GWO, the first part of the iterations is committed to investigation, and then the other part is committed to development. It overlooks the impact of the exact balance between the investigation and development that is guaranteed to an accurate estimate of the global optimum [21].

An Enhanced Gray Wolf Optimization algorithm (EGWO) with a better search scheme is proposed to overcome the limitation, which can be approached with a proper balance between investigation and development, leading to optimal algorithm performance and then shows that it generates the possible candidate solutions [22]. Figure 3 shows the lifetime of the network of the ES^2A and previous schemes. The graph depicts the analysis between the number of nodes in the network and the network lifetime in percentage. The red, blue, green, and purple line indicates the proposed IPSO, EBOA, EGWO and ES2A. The curves in the plot clear that up-to 800 no. of nodes from the 200, all the schemes are provided linearly increasing output. After unit 800, all the approaches are experiences constant output. But the proposed ES^2A algorithm achieves a higher lifetime of the network compared to other existing methods since it avoids the node with more traffic as shown in Table 2.

Table 2. Calculation of lifetime of the network vs. number of nodes.

Number of Nodes	IPSO	EBOA	EGWO	ES^2A
200	55.743	63.843	81.733	85.6922
400	62.464	72.043	86.374	89.1783
600	77.343	81.396	91.794	92.8478
800	88.673	91.353	96.756	98.6923
1000	89.422	93.362	97.254	99.6572

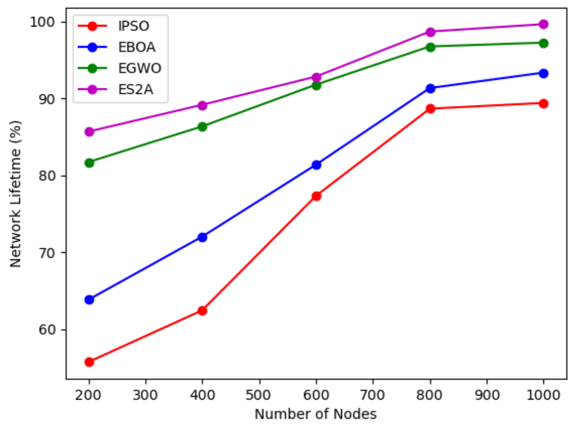

Fig. 3. Comparison of network lifetime for existing and proposed methods.

The analysis is made on energy consumption of the existing and the proposed ES^{2}A methods and depicted in Fig. 4. The X-axis shows the number of nodes taken for observation in the network, and the Y-axis represents the power consumption in joules. The energy utilized by the network corresponds to all the schemes are increased linearly when increasing the no. of nodes. In ES^{2}A, the inefficient nodes (i.e., the nodes with higher traffic, less energy) are dropped out from the current communication, which devoid the unnecessary retransmission of data packets and discovery procedures. Hence the proposed ES^{2}A approach achieves less energy consumption when compared to existing methods, as shown in Table 3.

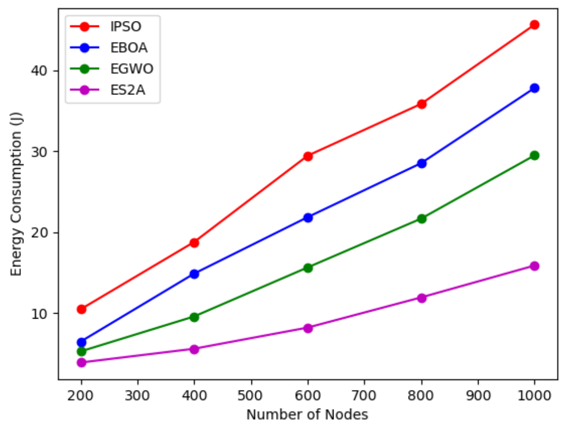

Fig. 4. Comparison of energy consumption.

Table 3. Calculation of energy consumption of the network vs nodes.

Number of Nodes	IPSO	EBOA	EGWO	ES^{2}A
200	10.458	6.458	5.2468	3.8726
400	18.782	14.872	9.5722	5.5782
600	29.458	21.855	15.636	8.1938
800	35.865	28.537	21.675	11.927
1000	45.672	37.838	29.500	15.872

Figures 5 and 6 shows the graphical representation of packet loss and packets delivery ratio, respectively. These two metrics are validated against the varying no. of nodes in the network from 200 to 1000. Since the ES2A scheme excludes the faulty nodes, the nodes with optimum constraints can communicate the data packets. It leads to a minimum no. of dropped packets. The curves of Fig. 5 indicate that the existing and proposed algorithms IPSO, EBOA, EGWO and ES^{2}A, respectively. Out of all the approaches, the dropping of transmitted packets is less than the remaining schemes. Similarly, due to packets' reduction, drop maximum no. of transmitted packets is received by the destination. Hence the proposed ES^{2}A achieves a high level of packets loss over the network compared to existing methods, as shown in Table 4.

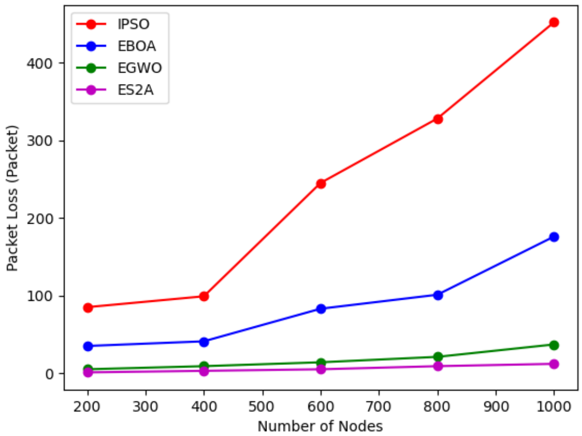

Fig. 5. Comparison of packet loss for existing and proposed methods.

Table 4. Calculation of packet loss of the network vs nodes.

Number of Nodes	IPSO	EBOA	EGWO	ES^{2}A
200	15.533	19.496	21.83	25.798
400	18.672	25.622	29.572	32.353
600	46.572	49.572	53.678	59.325
800	59.462	71.578	79.563	83.342
1000	72.678	83.783	97.230	98.024

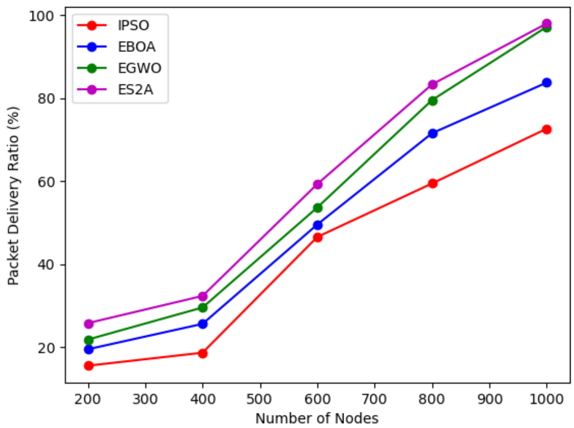

Fig. 6. Comparison of packet delivery ratio.

Figure 7 shows the throughput analysis of ES^{2}A and EPSO, EGWO, IBOA methods. The throughput of the ES^{2}A validated against the increment in no. of nodes of the network. The X-axis and Y-axis show the number of nodes in the network and the throughput performance in kbps. The proposed ES^{2}A optimizes the network by replacing the faulty node from its neighbour nodes. Hence within the time interval, all the packets transmitted from the source delivered to the destination. All the curves in Fig. 7 linearly increase when increasing the no. of nodes. But the curve that belongs to the ES^{2}A shows a higher level of packet delivery ratio when compared to existing algorithms, as shown in Table 5.

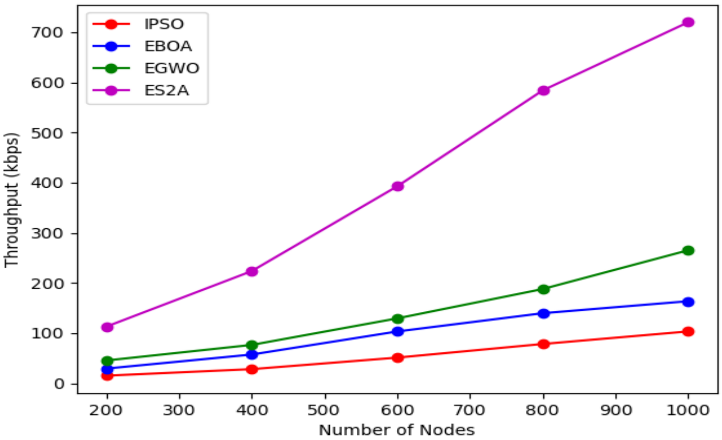

Fig. 7. Throughput for existing and proposed methods.

Table 5. Calculation of packet delivery ratio of the network vs number of nodes.

Number of Nodes	IPSO	EBOA	EGWO	ES^{2}A
200	85	35	5	1
400	99	41	9	3
600	245	83	14	5
800	328	101	21	9
1000	452	176	37	12

Figure 8 shows the overall performance of IBOA, EPSO, EGWO and ES^{2}A methods, respectively. The ES^{2}A method achieves better results than the existing methods due to network optimization with efficient faulty node replacement. Hence the proposed ES^{2}A method achieves 15.87% of power consumption, packet loss of 12%, packet delivery ratio of 98%, network life of 85.69% and throughput of 79.95% compared to other algorithms shown in Table 6.

Table 6. Calculation of throughput of the network vs number of nodes.

Number of Nodes	IPSO	EBOA	EGWO	ES^{2}A
200	15.252	29.354	45.522	112.876
400	28.273	57.3965	76.585	223.687
600	51.257	103.373	129.47	392.724
800	78.459	139.782	187.98	583.933
1000	103.46	163.733	265.29	719.950

Table-7 shows the overall comparison between proposed and existing methods.

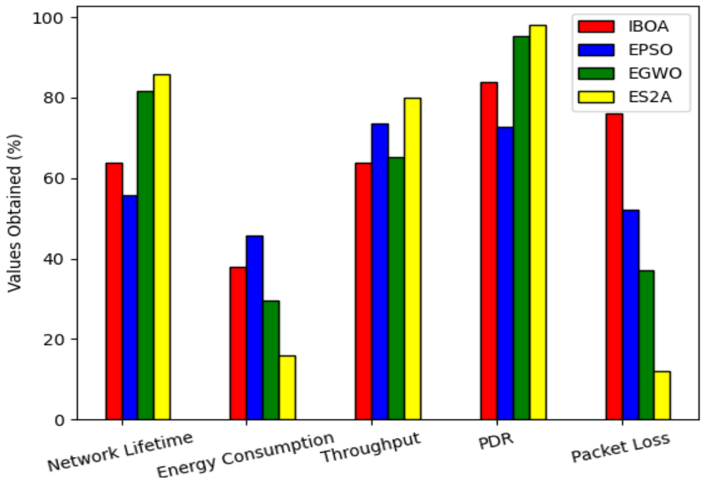

Fig. 8. Overall performance of existing and proposed methods.

Table 7. Overall performance of existing and proposed methods.

Method used	IBOA	EPSO	EGWO	ES^{2}A
Network Lifetime	63.84	55.74	81.73	85.69
Energy consumption	37.83	45.67	29.50	15.87
Throughput	63.73	73.46	65.29	79.95
Packet Delivery Ratio	83.78	72.67	95.23	98.02
Packet loss	76	52	37	12

5. Conclusion

Wireless Sensor Network directly influenced the lifetime of the network to optimize different aspects. This algorithm provides the solution for different aspects of the optimization problem of various metrics: the utilization of energy, lifetime of the network, delivery ratio of packets, packet loss and throughput. In this paper, the proposed Enhanced Spatter Swarm Algorithm (ES^{2}A) focuses on obtaining the optimal solution to improve the network lifetime and minimize energy utilization. By using optimum node replacement, the lifetime of the network is prolonged with the help of ES^{2}A. This paper sufficiently made a comparative analysis of ES^{2}A and the IBOA, EPSO, EGWO schemes. The numerical outcomes depicted in the Tables 1 to 6 proved that the proposed ES^{2}A outperforms better than the existing methods. In the future, to improve system performance, this technique can be integrated with artificial intelligence methods used for different applications. Moreover, the recommendation system can be extended for optimizing the number of levels, besides focusing on reducing the high frequency while replacing nodes and distributing CHs, determining how maximum energy for reducing the load on CHs closer to BS may be focused on the future further to improve the energy efficiency and overall lifespan of WSN.

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