

Minimizing the Energy Consumption of WSN Using Noble SMOWA-GA Algorithm

Sudip Kumar De, Asansol Engineering College, Asansol, India*

 <https://orcid.org/0000-0001-8390-9508>

Avishek Banerjee, Asansol Engineering College, Asansol, India

 <https://orcid.org/0000-0002-1019-6524>

Koushik Majumder, Maulana Abul Kalam Azad University of Technology, West Bengal, India

Samiran Chattopadhyay, Institute for Advancing Intelligence, TCG Crest and Jadavpur University, West Bengal, India

ABSTRACT

In this paper, the authors have concentrated on the practical application of optimization problems related to the minimization of the energy consumption of WSN. Here a noble algorithm called self-adaptive multi-objective weighted approach-genetic algorithm (SMOWA-GA) is proposed to resolve the optimization problem. A multi-objective optimization problem was chosen as the subject of this research. The main objective of the paper is to propose and apply different WSN node deployment strategies to design an efficient wireless sensor network to minimize the energy consumption of the whole WSN. The statistical analysis also has been carried out on the obtained data of the optimization techniques. To analyze the obtained result a statistical tool, Wilcoxon rank-sum test has been used. The Wilcoxon rank-sum test assists in determining whether the population chosen for the experiment (SMOWA-GA) is accurate. The statistical analysis also will help the reader to gather a detailed analysis of obtained data from the multi-objective energy-efficient optimization problem.

KEYWORDS

Energy Minimization, Optimization Technique, Self-Adaptive Multi-Objective Weighted Approach With Genetic Algorithm (SMOWA-GA) Algorithm, Statistical Analysis, Wireless Sensor Network (WSN)

1. INTRODUCTION

The wireless sensor network may be thought of as a decentralized network system with several sensor nodes and central sink node(s) distributed over an area (Wang et al. 2017). A sensor node is made up of five major components: a sensing unit, digital data storage unit, energy supply unit, transceiver unit, and a limited computation unit. Navarro et al. report that particular types of sensors are attached to the nodes to sense the activities of the external environment. Depending on the application, many types of sensors are attached to the nodes. The sensing unit collects environmental data using various

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*Corresponding Author

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sensors and acts as the input device of the network. The sensor's collected data is processed by the small processor, which then outputs the processed data (Sara et al. 2016). The data storage unit is used to store processed data in the local storage unit of the node. In general, the data storage capacity of WSN nodes is quite low (Ren et al. 2018). The transceiver unit sends and receives a limited quantity of processed data to nearby nodes or the sink node. The energy supply unit is responsible for supplying power to each unit of the WSN node. This self-contained battery power source is used to keep the node operational (Visconti et al. 2016). The sink node performs the function of the processing center. To build the network and establish a communication link, the sink node can communicate with each node. It sends and receives data to and from the dominating nodes. This type of network system is classified as a multi-hop communication system (Kumar et al. 2018).

In the modern era, Wireless Sensor Network (WSN) is also widely used in various fields like agriculture, meteorology, modern-day army, environmental monitoring, battlefield monitoring, body area network, intelligent household, etc. The WSN can be applied for many purposes: air pollution detection, fire detection, health monitoring, threat detection, etc. The WSN has a lot of applications in smart city projects also. The efficient implementation of WSN in a smart city can make the surveillance system which can reduce or stop unwanted events. As a result, a well-functioning efficient WSN is in high desire. But the design of the efficient WSN is not so easy. To configure a good WSN the hardware and software engineers should come up with experienced mathematicians or researchers having enormous knowledge of optimization and statistics. For many decades, optimization has been regarded as the most promising field of study, Bangyal et al. (2021). Optimization-based methods and statistical analytics are enormously used in the field of engineering. When a WSN system would be designed then the obvious question would be the sustainability (how long WSN can be in functioning status) of the system. Sustainability can be defined as the probability of persistency. One of the parameters of sustainability in the WSN system is energy. Energy is very limited in WSN. If the network's energy consumption can be minimized, the system's durability and sustainability can be improved, allowing the WSN to operate for longer periods. So, in this research work, the minimization of energy consumption (one of the essential measures) in a WSN has been chosen to prolong the sustainability of the network. To do energy minimization a multi-objective optimization approach has been considered. The node deployment strategy also has a significant impact on total energy usage in network communication. In this research, two types of deployment strategies have been used (Random deployment and U pattern deployment) to observe and compare the impact of energy consumption on the network.

The statistical analysis also has been carried out on the obtained data of the optimization algorithm. Now the very important question is that how a statistical tool can help in WSN design? Using this statistical analysis, the researchers can easily select the right objective function value for the energy minimization problem. The statistical approach will also enable the developer to make the right decision on hardware implementation. To determine if the findings of the proposed method were statistically significant, the authors, Seyedali Mirjalili et al (2014), utilized the Wilcoxon Rank-Sum statistical test. As a part of statistical analysis, the statistical tool, the Wilcoxon Rank-Sum test, has been used in this research.

The main aim of this research paper is to prolong the sustainability of the network by minimizing the network's overall energy consumptions. The research methodology can be briefly described in the following way.

To begin with, the indexing of WSN nodes has been performed to keep track of all WSN nodes. Following the indexing, the target region has been clustered to reduce the amount of energy spent by WSN nodes. After clustering of the target area, the deployment of WSN nodes on the clustered target area has been carried out. Two types of deployment strategies have been used: Random deployment and U pattern deployment. After that, the proposed SMOWA-GA algorithm is applied to minimize the consumed energy of the whole WSN network. It has been observed that the number of active day-life of the WSN network is higher in the case of U pattern deployment strategy than Random

deployment strategy. To analyze the obtained result a statistical tool, Wilcoxon rank-sum test has been used to determine whether the population chosen for the experiment (SMOWA-GA) is accurate or not.

Contribution: The contributions of the paper are as follows:

- Prolonging the sustainability of the network by minimizing the energy consumption in the WSN using a noble hybrid multi-objective optimization technique i.e., Self-adaptive Multi-Objective Weighted Approach-Genetic Algorithm (SMOWA-GA).
- The total population has been segregated into multiple populations. The self-adaptive characteristic of the algorithm is used to enhance the quality of the population by choosing the better population from the available population sets. The multi-objective nature of the algorithm has been used to address two different propagation models (free space propagation and two ray propagation model).
- The Genetic Algorithm (GA) has been used for its efficient search capability of finding global optimized value using its powerful robust operators (crossover, mutation, selection). So, in this research to get the best possible solution for the defined problem, the GA has been used.
- The hybridization of two algorithms, SMOWA and GA, has been carried out and the SMOWA-GA algorithm has been developed. The SMOWA portion of the algorithm is used to screen the population, based on the qualitative nature of the populations; the higher the quality of the population, the better the solution. Once SMOWA provides a better population set, then GA has been applied to those specific populations to get even better results.
- Previously, no researcher has concentrated on the hybrid algorithm (SMOWA-GA) to minimize the consumed energy of the WSN, and it has been observed that the suggested algorithm outperforms the present literature (Banerjee et al. 2021b).

The paper is organized with several sections such as “Literature Survey” in section 2. In section 3, the “Problem Formulation” has been described. In section 4, the “Solution Procedure” of the problem has been defined. In section 5, the “Methodology” has been discussed. In section 6, “Numerical Solutions and Discussion” has been deliberated. In section 7, the “Experimental Results” has been plotted. In section 8, the “Result Analysis” has been done. The “Conclusion” has been presented in section 9.

2. LITERATURE SURVEY

In recent decades, there has been a tendency in the research world to use bio-inspired metaheuristic optimization methods to handle complicated optimization issues, Stojanović et al. (2017). Various Metaheuristic techniques such as the Genetic algorithm, Particle swarm optimization (Matin et al. 2017), Bat algorithm (Bangyal et al. 2019) are extensively applied in estimated search strategies to solve complicated optimization issues. It also has been noticed that in recent research works, multi-objective optimization approaches are mostly taken to obtain a better result. Matin et al. (2017) demonstrate that the multi-objective optimization method outperforms the single-objective optimization method.

To maintain energy efficiency in WSN, Mehta et al. (2020) propose a multi-objective optimization method. Multiple objective functions have been used to find out the fitness function value. Depending on an effective fitness function value the cluster head is selected. After the selection of the cluster head, the sailfish optimizer is used for selecting the best possible path to sink node for data transmission. Due to this approach number of dead sensor nodes is decreased and the energy consumption is reduced also. In Rao et al. (2017), another novel chemical reaction optimization technique has been used to optimize energy consumption through the selection and formation of cluster heads. For the formation of the clusters, different distance parameters like sink distance, intra-cluster distance, and energy parameters are considered for enhancing energy efficiency. At the time of packet transmission between different sensor nodes, there lies a question of safe transmission. Borkar et al. (2019) addressed the

safety issue related to packet transmission. Here the authors had used an adaptive swarm optimization algorithm to select the cluster heads. The problem of packet safety at the time of transmission has been overcome by their approach. Recently, numerous research studies have been done using the multi-objective optimization technique. A study of recent research works and progresses on this matter has been carried out by Fei et al. (2016) in his paper. In that paper different important optimization objectives have been addressed. The different multi-objective approaches and advanced optimization techniques are also discussed. In that paper, the varieties of recent research investigations are most significantly summarised. To achieve better efficiency and accuracy of the position of nodes, a localization approach has been taken by Shahzad et al. (2016). The multi-objective optimization functions are formulated and used to reduce localization errors and the number of transmissions overhead during the localization phase. Various anisotropic and isotropic topologies have been used to get the performance of the proposed approach. Existing studies and research works are analyzed in Iqbal et al. (2016) to show current trends of technologies, applications, and simulation tools used in sensor networks. A generic resource allocation problem is presented with input, output, and constraints variables. A multi-objective optimization approach has been also discussed in that paper.

The multi-objective optimization approaches are also used for security and quality of service in WSN. In Rachedi et al. (2016), the factors of security cost have been discussed. Those factors are energy consumption, execution time, quality of service, etc. A new solution has been proposed using a Genetic algorithm with a multi-objective optimization technique. In another paper, Khalil et al. (2017), proposed a technique for the construction of an energy-efficient virtual backbone network while improving network reliability. To increase both factors (reliability and energy efficiency), the multi-objective optimization method is used. This paper provides higher reliability, higher stability, and an energy-efficient virtual backbone network. In Singh et al. (2018), a multi-objective optimization function is also used to implement a congestion control algorithm. The energy of the node has been optimized as well as the optimization of the data transfer rate has been considered. As the deployment of the sensor nodes is one of the major factors in terms of area coverage, power consumption, and battery life to achieve a better WSN, the researchers have done their works on deployment strategies also. The recent works on different deployment strategies have been discussed and compared in Abdollahzadeh et al. (2016). The challenges, drawbacks, benefits of different deployment strategies also have been analyzed. Aznoli et al. (2017) also analyzed different challenges and factors related to the deployment of the sensor nodes. In this paper, several deployment strategies and challenges are investigated and discussed. Another work on deployment strategies was also done by Rahman et al. (2016). Two different types of deployment strategies (corona and non-corona-based) have been discussed and compared with the others. Ouchitachen et al. (2017) proposed an algorithm that reduces energy consumptions and the lifetime of the network has been increased. Here the network is divided into some clusters and then sensors have been selected depending on the best performance. The performance of the sensors is dependent on residual energy for communication with the base stations. It has also been found that hybridized algorithms (Khattak et al. 2021) provide better results in various fields. Bangyal et al. (2020) proposed a hybridization algorithm, TW-BA, that has a higher convergence rate and produces more consistent results than non-hybridized algorithms. When the Contraceptive method choice (CMC) algorithm is combined with Particle swarm optimization (PSO), the hybridized algorithm performs better in terms of classification accuracy, Bangyal et al. (2012).

Following a thorough examination of the aforementioned research papers and articles, it is observed that little development has been done to address the problem of constructing energy-efficient WSNs utilizing hybrid algorithms. Using the hybrid optimization technique, Banerjee et al. 2021b, suggested a single objective function to minimize consumed energy and coverage area optimization.

In this research work, the multi-objective function using a hybrid algorithm has been used to minimize the energy requirements of the WSN for prolonging the sustainability of the network.

3. PROBLEM FORMULATION

In this paper, a multi-objective function has been proposed to minimize the consumed energy of WSN utilizing the SMOWA-GA algorithm with Random and U pattern deployment strategies. The multi-objective function has been described by Eq (1).

In the existing literature, there are numerous methods for solving multi-objective optimization problems. In those methods, the “multi-objective optimization problems” have been expressed as different types of scenarios. Some of these scenarios are as follows:

Scenario 1: Global criteria method.

Scenario 2: Weighted method.

Scenario 3: ε -Constraint method.

Scenario 4: Weighted sum method.

All these methods are posterior i.e., all these methods generate Pareto optimal solutions. For a detailed discussion about the multi-objective optimization problem, one may refer to the book of K. Miettinen (2012).

In this paper the modified posterior method has been proposed to formulate the multi-objective nonlinear constrained optimization problem as follows:

$$F(D, d) = \text{Minimize} \sum_{i=1}^k w_i \left(\left| f_i(x_1, x_2, x_3, \dots, x_n) - f_i^* \right| \right) \quad (1)$$

subject to:

$$\sum_{i=1}^k w_i = 1$$

where, $w_i \geq 0, i = 1, 2, \dots, k$ and $x \in S$.

f_i^* is the ideal objective value of the objective function $f_i(x)$ (Sahoo et al. 2014).

This method looks like a weighted approach introduced by Charnes and Cooper in 1977.

In this problem, the weighted component has been adjusted by prior choices of objective functions. This may be considered in several ways.

Way 1: The Second constraint is more important than the first i.e., $w_1 < w_2$.

Way 2: The First constraint is more important than the second constraint i.e., $w_2 < w_1$.

Way 3: The First constraint is equal to the second constraint i.e., $w_2 = w_1$.

In this research work, only Way 3 has been implemented to solve the existing multi-objective problem. In the future, one can work on Way 1 & Way 2.

The reduced optimization problem can be written as follows:

$$\text{Min}(f_1, f_2) = \text{Minimize} \left(w_1 * \left(E_{\text{communication}}^{\text{Total-FS}}(D, d) \right) + w_2 * \left(E_{\text{communication}}^{\text{Total-TR}}(D, d) \right) \right) \quad (2)$$

subject to $d \leq d_0$, for the Free-space propagation model and $d > d_0$, for the Two-ray ground propagation model. where d_0 is the threshold transmission distance.

Function $f1$ denotes energy consumption during the Free-space propagation model.

Function $f2$ denotes energy consumption during the Two-ray ground propagation model.

The proposed method has been used to minimize the consumed energy for WSN. During data transmission, it is obvious that energy is required to transfer data between WSN nodes. The energy consumption during successful data transmission among different WSN nodes has been designed and optimized using the below-mentioned equations (Banerjee et al. 2021b):

$$f1(D, d) = \text{Minimize} \left(E_{communication}^{Total_FS} (D, d) \right) \quad (3A)$$

$$f2(D, d) = \text{Minimize} \left(E_{communication}^{Total_TR} (D, d) \right) \quad (3B)$$

subject to $d \leq d_o$, for the Free-space propagation model and $d > d_o$, for the Two-ray ground propagation model where d_o is the threshold transmission distance and D is the data transmission rate.

The total consumed energy for the total communication can be expressed by the following equation:

$$E_{communication}^{Total} (D, d) = E_{receiving}^{Total} (D) + E_{transmission}^{Total} (D, d) \quad (4)$$

In the research work, in the case of the Two-ray propagation model, the distance between two nodes has been considered in-between permissible ranges i.e., 50 meters to 100 meters (Naranjo et al. 2017).

Depending on the propagation model the Eq. (4) can be expressed as follows:

$$E_{communication}^{Total_FS} (D, d) = E_{receiving}^{Total_FS} (D) + E_{transmission}^{Total_FS} (D, d) \quad (4A)$$

$$E_{communication}^{Total_TR} (D, d) = E_{receiving}^{Total_TR} (D) + E_{transmission}^{Total_TR} (D, d) \quad (4B)$$

3.1 Equations of Energy Consumption in Free-Space Propagation Model (where $d \leq d_o$)

$$E_{communication}^{Total_FS} (D, d) = E_{receiving}^{Total_FS} (D) + E_{transmission}^{Total_FS} (D, d)$$

$$E_{receiving}^{Total_FS} (D) = E_{charge}^{FS} (D) * (D) \quad (5)$$

$$E_{transmission}^{Total_FS} (D, d) = E_{charge}^{FS} (D) + E_{resonator}^{FS} (D, d) \quad (6)$$

$$E_{transmission}^{Total_FS} (D, d) = E_{charge}^{FS} (D) + E_{tfs}^{FS} * d^2 \quad (7)$$

where:

$$E_{resonator}^{FS}(D, d) = E_{tfs}^{FS} * d^2 \quad (8)$$

where:

$$E_{tfs}^{FS} = 10pJ * bit - 1 * m - 2 \quad (9)$$

3.2 Equations of Energy Consumption in Two-Ray Ground Propagation Model (where $d > d_0$)

$$E_{communication}^{Total_TR}(D, d) = E_{receiving}^{Total_TR}(D) + E_{transmission}^{Total_TR}(D, d)$$

$$E_{receiving}^{Total_TR}(D) = E_{charge}^{TR}(D) * (D) \quad (10)$$

$$E_{transmission}^{Total_TR}(D, d) = E_{charge}^{TR}(D) + E_{resonator}^{TR}(D, d) \quad (11)$$

$$E_{transmission}^{Total_TR}(D, d) = E_{charge}^{TR}(D) + E_{ttr}^{TR} * d^4 \quad (12)$$

where:

$$E_{resonator}^{TR}(D, d) = E_{ttr}^{TR} * d^2 \quad (13)$$

where:

$$E_{ttr}^{TR} = 0.0013pJ * bit - 1 * m - 2$$

$E_{resonator}$ = The energy needed for the transmitting data packets between two adjacent WSN nodes after amplifying and maintaining the acceptable “signal-to-noise ratio”

E_{charge} = Energy disbursed during the transmission between two adjacent WSN nodes

$E_{transmission}$ = The amount of energy disbursed by WSN nodes for transmitting data packets

$E_{receiving}$ = The amount of energy consumed by WSN nodes for receiving data packets

$E_{communication}^{Total_TR}$ = Amount of consumed energy by single WSN node for Two-Ray ground propagation

$E_{communication}^{Total_FS}$ = Amount of consumed energy by single WSN node for Free-Space propagation model

Measurement of distance between two WSN nodes is measured by:

$$d = \sqrt{(x1 - x2)^2 + (y1 - y2)^2}$$

where $(x1, y1)$ and $(x2, y2)$ are coordinates of WSN nodes and d is the distance between two adjacent WSN nodes.

For solving the problem, the hybrid SMOWA-GA algorithm has been used and it is being discussed in the Solution Procedure section.

4. SOLUTION PROCEDURE

The following describes the Solution Procedures of the proposed work:

4.1 Indexing of WSN Nodes

The WSN nodes would be deployed on the target area. To keep track of every WSN node the indexing of all WSN nodes has been done. For indexing, sequential serial numbers [e.g., 1,2, 3.....n] have been used.

4.2 Clusterization

The target area is a type of area where WSN nodes are deployed. To manage overall performance, the target area is typically divided into many uniform blocks known as clusters. After the indexing process of WSN nodes, the target area has been divided into clusters. The outcomes of the clusterization process are some clustered target areas.

4.3 Deployment of WSN Nodes

Indexed WSN nodes are deployed in the clustered target areas. The start and end time of the deployment process in the clustered target area is considered as login time and logout time respectively. The deployment time is the difference between logout and login time. The following deployment strategies have been considered:

1. **Random deployment:** The nodes are deployed randomly in the clustered target areas within a threshold deployment time.
2. **U pattern deployment:** The nodes are deployed in U shape pattern in the clustered target areas within threshold deployment time.

4.4 Minimization of Consumed Energy of WSN Using SMOWA-GA Algorithm

After the deployment of WSN nodes, the wireless sensor network is configured following the random and U-pattern deployment strategies. Following that, the SMOWA-GA Algorithm has been applied to minimize the energy consumption by different WSN nodes. The chromosome used in the algorithm has been constructed using different parameters of WSN nodes such as the threshold distance (d_0) of communication and data transmission rate (D).

4.5 Statistical Analysis

Statistical analysis always plays an important role in any kind of scientific research. To analyze the obtained result a statistical tool, the Wilcoxon rank-sum test has been used. The Wilcoxon rank-sum test has been applied to the chosen populations to analyze the results to determine whether the population chosen for the experiment (SMOWA-GA) is accurate.

5. METHODOLOGY

In this paper, the SMOWA-GA algorithm has been used to minimize the energy consumptions of WSN nodes. The SMOWA-GA algorithm has been applied to a multi-objective problem which is already described in the previous section. The SMOWA-GA algorithm is the combination of two algorithms i.e., Self-adaptive Multi-Objective Weighted Approach (SMOWA) and Genetic Algorithm (GA).

The self-adaptivity capability of the algorithm makes the algorithm the best fit for the multi-objective problem. The solution space for the multi-objective function is dependent upon the quality of the population used in different generations. If the quality is high, generally the solution can easily converge to the global optimum value. Rauf et al. employed an adaptive population initialization strategy in 2021 to maintain a reasonable level of population diversity.

In this research work, each population of the self-adaptive algorithm is segregated into equal, n number of sub-populations depending upon the quality of the solutions. If the quality of the solution is increased then the sub-population gets higher priority than other sub-populations. The quality of the solution is measured on predefined threshold values of the solution space and the threshold values are achieved through the ideal fitness function. In a self-adaptive algorithm, higher priority populations are selected automatically for the betterment of global convergence. Step 3 of the SMOWA-GA Algorithm describes the self-adaptivity capability of the algorithm which makes the algorithm best fit for the multi-objective problem by finding the local optimal which is passed to the GA algorithm for global search.

Various evolutionary computing (EC) methods are gaining popularity for great global exploration capability (Bangyal et al. 2018). In a hybrid algorithm, the GA is used as a global search algorithm over the other local search optimization technique. In this research work, the same strategy has been adapted. In this algorithm (SMOWA-GA), the local search is being carried out by the SMOWA algorithm, and the solution obtained by SMOWA is fed into the GA algorithm to carry out the global search. In step 4, the GA is involved which inculcates the global search nature to the proposed hybrid algorithm. In this hybridized process, there is very little chance to miss any local optima value as well as the global optima value of the solution space.

The amalgamation of these two algorithms (SMOWA & GA) has been described in the subsection entitled “SMOWA-GA Algorithm for solving a multi-objective problem”.

5.1 SMOWA-GA Algorithm for Solving a Multi-Objective Problem

Step 1: Initialize the populations and set the termination condition (i.e., the maximum number of fitness function (Eq. (1)) evaluations)

Step 2: Compute the initial candidate solutions based on the value of the defined fitness function for the problem.

Step 3: Each population is segregated into equal, n number of sub-populations depending upon the quality of the solutions. The segregation process is carried out using an operator called a segregation operator. The quality is measured on predefined threshold values and the threshold values are achieved through the ideal fitness function (see Eq. (1)).

Step 4: For Each sub-population perform the following Genetic Algorithm.

Step 4.1: Initialize: the population size (P_s) , the maximum generations (M_g) , crossover percentage (P_c) , mutation percentage (P_m) , and the decision variables.

Step 4.2: Initialize the generation as $t = 0$.

Step 4.3: Calculate the value of fitness function for each chromosome of the population $P(t)$.

Step 4.4: $t = t + 1$

Step 4.5: Calculate the value of fitness function for each chromosome of the population $P(t + 1)$.

Step 4.6: Choose the best chromosomes between $P(t)$ and $P(t + 1)$ store it.

Step 4.7: Crossover and Mutation operators are applied between $P(t)$ and $P(t + 1)$.

Step 4.8: Selection operator is applied between $P(t)$ and $P(t + 1)$.

Step 4.9: If the “Termination condition” is satisfied then go to step 5, else go to step 4.4.

Step 5: Fitness value is determined depending on Eq. (1).

Step 6: In the selection phase the selection operator is used where the modified solutions are accepted if the modified solution is better than the old solution. Here the modified solution refers to the $Current_{best}$ solution and the old solution refers to the best solution of the previous generations.

Step 7: Check the termination condition(s). If the limit of fitness function evaluation exceeds, then end the process and display the best solution; otherwise, go to step 3 to re-segregate the population.

Step 8: End

6. NUMERICAL SOLUTIONS AND DISCUSSION

To illustrate the proposed approach for solving constrained multi-objective optimization problem by the SMOWA-GA algorithm, the following numerical example (Banerjee et al. 2021b) has been considered.

The input values for the experiment's various parameters are shown in Table 1. The parameters have been chosen from the existing literature (Banerjee et al. 2021b). After applying different deployment strategies (Random pattern & U pattern), the following networks have been generated.

7. EXPERIMENTAL RESULTS

The proposed hybrid algorithm (SMOWA-GA) has been run successfully 20 times to get the best result. The problem (see Eq. (2)) has been solved considering the feasible set of constraints (see Eqs. (3)-(13)). The proposed hybrid algorithm (SMOWA-GA) has been implemented using the python programming language in the Anaconda IDE in the Windows operating system. In this experiment/simulation, a run is considered as a successful run if the obtained solution value of the problem is either the same value or better than the known best-found solution value. The obtained numerical data of results are being represented with the help of tabular format as depicted in Table 2.

8. RESULT ANALYSIS

The SMOWA-GA algorithm has been applied to minimize consumed energy and to maximize the day-life of the total WSN. Here the day-life refers to the lifetime of the total WSN. Experiments have been carried out using 400 nodes and two types of deployment strategies have been used: Random deployment & U pattern deployment. From Table 2 it is observed that the lifetime of the constructed WSN, is 9.41 days, 9.91 days, 6.33 days, and 8.39 days for the SMOWA-GA (using random deployment), SMOWA-GA (U pattern deployment), modified ACO (Banerjee et al. 2021b) and GA algorithm respectively. With respect to the current literature (Banerjee et al. 2021b), the SMOWA-GA (using random deployment) has a 48.66 percent lifetime improvement, the SMOWA-

Table 1. Input parameters

Parameter	Value	Parameter	Value
Size of target area	950 x 950 m ²	Data packet size (k)	512bytes
Total sensor nodes	81	Max no. of nodes	400
Initial energy	1J	E_{charge}	50nJ/bit
E_{tfs}^{FS}	10pJ * bit ⁻¹ * m ⁻²	E_{ttr}^{TR}	0.0013pJ*bit ⁻¹ *m ⁻²

Figure 1. Random deployment [Banerjee et al. 2021b] of 400 nodes (before building a network among nodes)

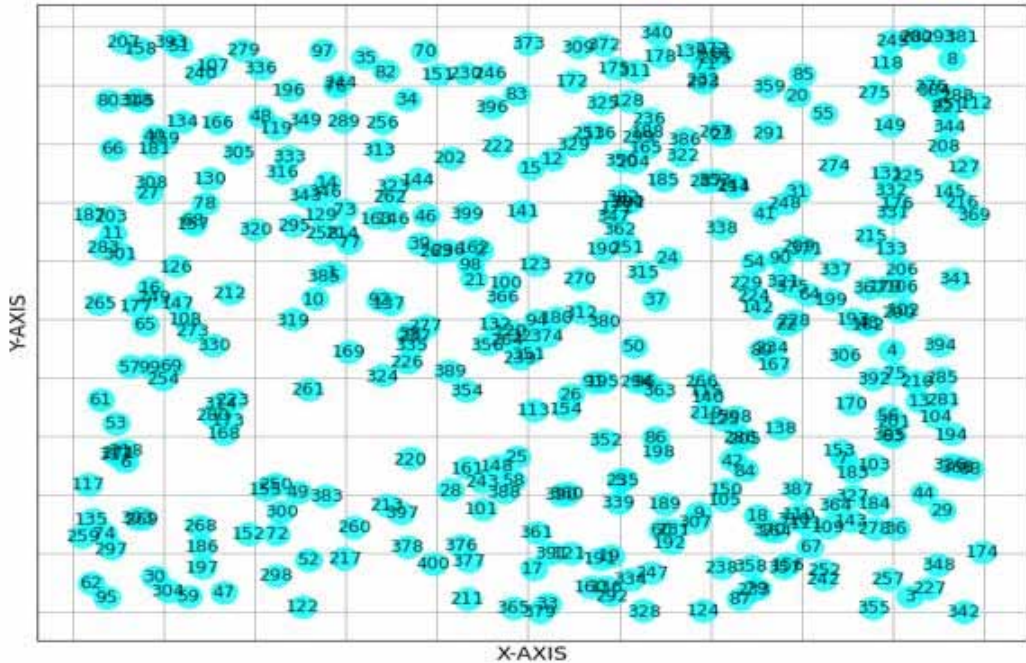


Figure 2. Establishing a network with 400 randomly [Banerjee et al. 2021b] deployed WSN nodes

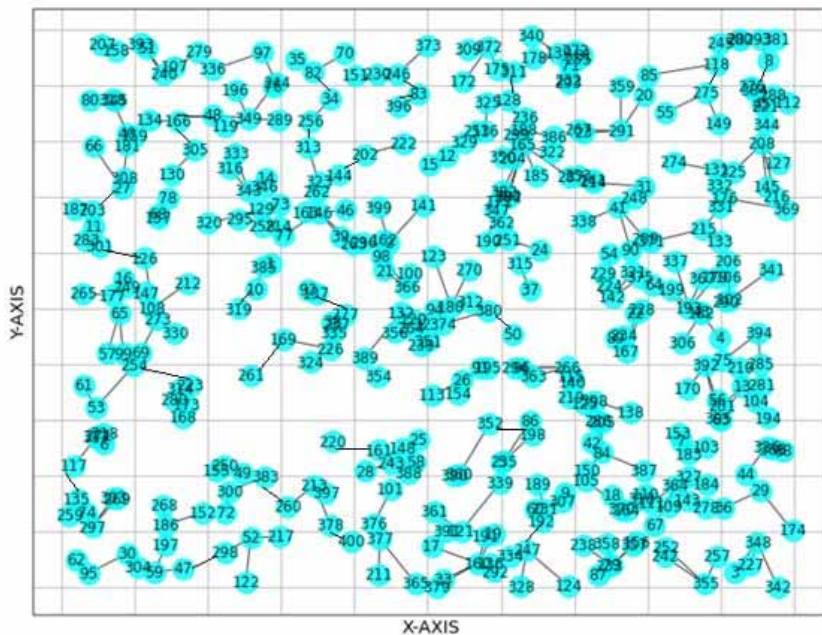


Figure 3. U pattern [Banerjee et al. 2021b] deployment of 400 nodes (before building a network among nodes)

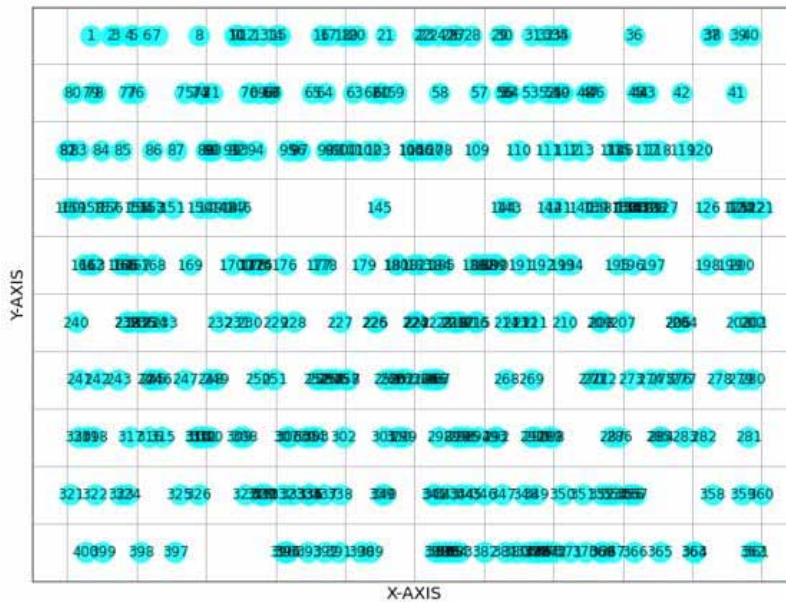


Figure 4. Connection building among 400 U patterned [Banerjee et al. 2021b] deployed WSN nodes

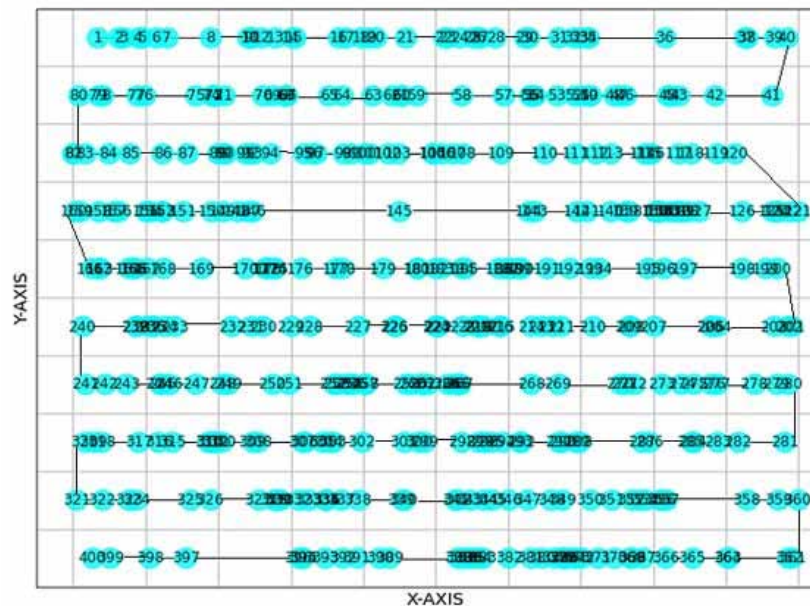


Table 2. Results obtained for different algorithms and their comparisons

Parameters	Result of SMOWA-GA algorithm to minimize consumed energy in case of deployment of 400 nodes using		Result of modified ACO algorithm to minimize consumed energy in case of	Result of GA algorithm to minimize consumed energy in case of	Improvement in lifetime
	Random deployment	U pattern deployment	217 randomly deployed nodes [Banerjee et al. 2021b]	217 randomly deployed nodes	
Total initial energy	4.0* E+14	4.0* E+14	2.17E+14	2.17E+14	48.66%, 56.56% and 32.54% improvement in lifetime with respect to [Banerjee et al. 2021b]
Nodes required to configure the WSN	81	81	49	65	
Total energy / consumed energy per sec (Lifetime of the network in sec.)	185613 (Median value)	193888 (Median Value)	124118 (Median Value)	164646 (Median Value)	
Total energy / consumed energy per hour (Lifetime of the network in an hour)	51.56	53.9	34.48	45.73	
Total energy / consumed energy per day (Lifetime of the network in a day)	2.15	2.24	1.43	1.89	
Total number of the day life	9.41	9.91	6.33	8.39	

GA (using U pattern deployment) has a 56.56 percent lifetime improvement, and the GA has a 32.54 percent lifetime improvement.

In a multi-objective optimization problem, there is a high chance to obtain a set of optimal solutions. Finding out the superior one from them is a hard job. To simplify the selection of a superior optimal solution the Pareto-front technique has been used. Through the Pareto front analysis, it can be understood that the solutions which are not close to the Pareto front line are never the best. In contrast, the solutions which are close to the Pareto front line could be the best alternative. The Pareto front is the set of the optimal solutions in the space of objective functions in the multi-objective optimization problem domain. Each optimal solution of the Pareto front technique is known as the Pareto point. When all the feasible Pareto points are connected then a curve is obtained, which is known as Final Pareto. The Final Pareto represents the different solutions of the multi-objective function for different parameter spaces. Among those Pareto points in the final Pareto curve, one Pareto point is chosen which will balance all the internal factors is called the Final Pareto point.

The Final Pareto and the Final Pareto Point of SMOWA-GA algorithm after 5 runs, 10 runs, 15 runs & 20 runs have been shown in Fig 5A-5B, Fig 6A-6B, Fig 7A-7B, Fig 8A-8B respectively. In those figures, the X-axis represents f_1 which denotes energy consumption during the free-space propagation model and the Y-axis represents f_2 which denotes energy consumption during the two-ray ground propagation model. Considering the multi-objective functions (f_1 & f_2) different final Pareto points are identified which denote the optimal solution for the given problem.

To analyze the obtained result further, the statistical tool, Wilcoxon rank-sum test has been used. The Wilcoxon rank-sum test assists in determining whether the population chosen for the experiment (SMOWA-GA) is accurate or not.

Figure 5. (a) The final pareto of the SMOWA-GA algorithm after 5 runs (b) The final pareto front of the SMOWA-GA algorithm after 5 runs

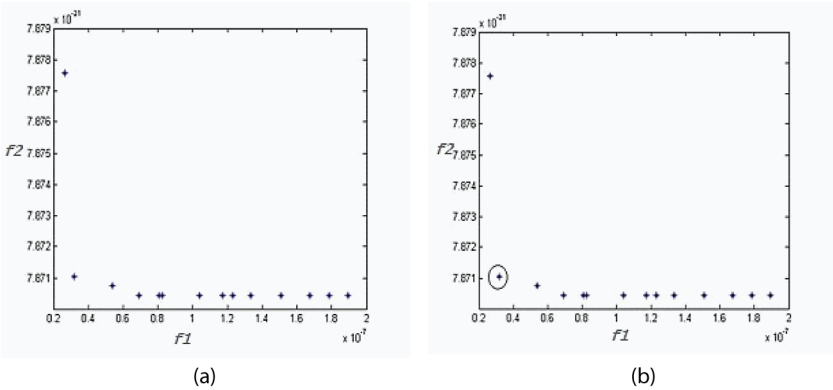


Figure 6. (a) The final pareto of the SMOWA-GA algorithm after 10 runs (b) The final pareto front of the SMOWA-GA algorithm after 10 runs

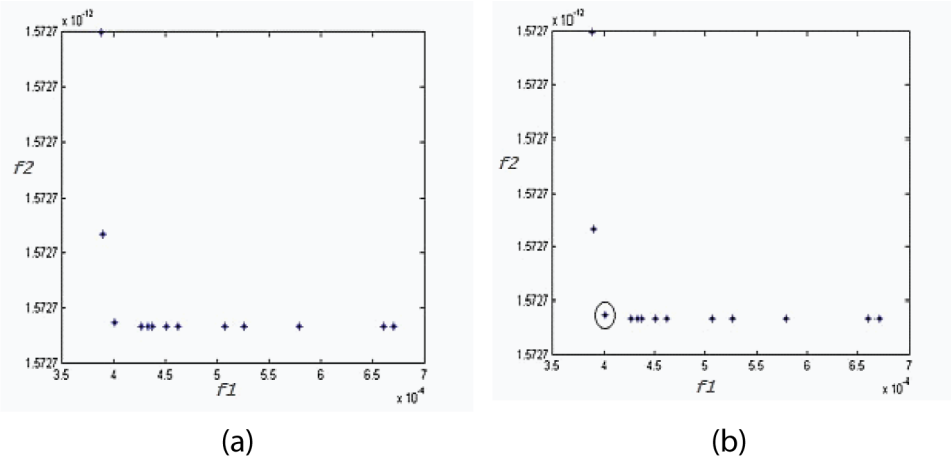


Figure 7. (a) The final pareto of the SMOWA-GA algorithm after 15 runs (b) The final pareto front of the SMOWA-GA algorithm after 15 runs

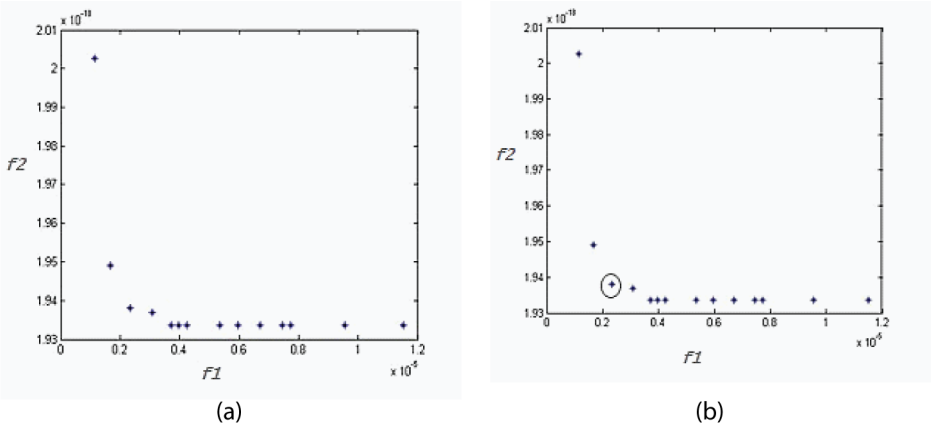
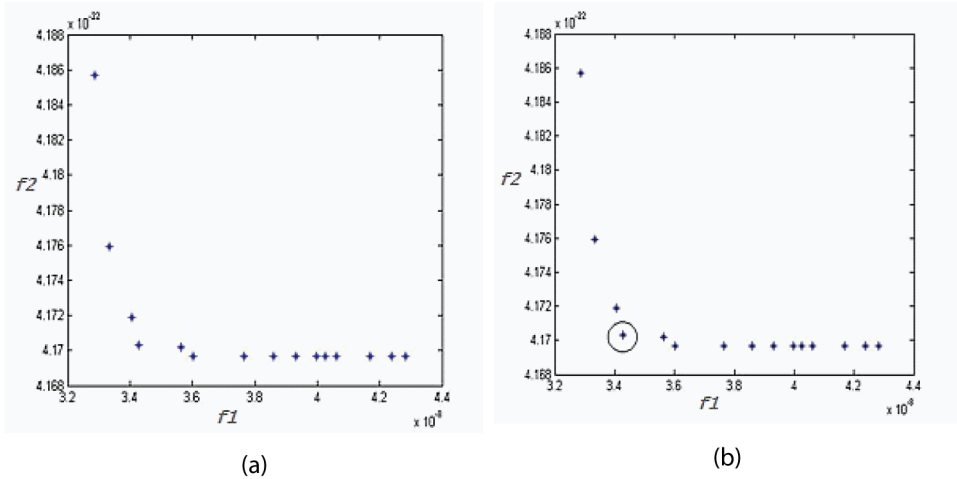


Figure 8. (a) The final pareto of the SMOWA-GA algorithm after 20 runs (b) The final pareto front of the SMOWA-GA algorithm after 20 runs



8.1 Wilcoxon Rank-Sum Test for the Multi-Objective Problem

The Wilcoxon Rank-Sum Test has been performed on the obtained result of the SMOWA-GA algorithm where the referred population $P(t)$ is an instance of the population set (Ps) . In this algorithm, the value of $w1$ & $w2$ is 0.5 for the proposed model. For the suggested model, the values of $w1$ and $w2$ are set to 0.5 since it is assumed that both propagation models, “two-ray propagation model” and “free-space ground propagation model,” have been considered equally. Depending on the nature of the target area, the balance between these two propagation models can be chosen in the future.

The generated population for the SMOWA-GA algorithm, in the case of Random and U pattern deployment for 400 nodes, is denoted by Population1 and Population2 respectively. Population 3 is the population generated for the Ant Colony Optimization (ACO) algorithm (Banerjee et al. 2021b) for a random deployment of 217 nodes. Population 4 is the population generated for the Genetic algorithm (GA) method for a random deployment of 217 nodes. Table 3 shows the objective function values and rank for different populations on different runs. The data in Table 3 have been used in Wilcoxon Rank-Sum Test to generate the p-value. The p-value is used to decide the significance of the performance of the populations.

According to Wilcoxon Rank-Sum Test (Wilcoxon et al. 1970) if the p-value for one population is less than the p-value for another, then the population with the lower p-value shows higher performance. Table 4 shows the parameters used to calculate the p-values for Populations 1, 2, 3, and 4. From the p-value, it can be decided which population of the experiments gives better day-life survivability.

From Table 4, it can be noticed that the p-value for Population 2 is lesser than ($<$) the p-value of Population1, Population 3, and Population 4. Therefore, Population 2 (sample) has higher significance over Population 1, Population 3, and Population 4. So, from the p-value, it can be decided that Population 2 of the experiment gives better day-life survivability. The same thing has also been established through the proposed SMOWA-GA algorithm. The “Total number of the day-life” field of Table 2, shows that the U pattern deployment strategy of the SMOWA-GA algorithm (Population 2) has the highest sustainability (i.e., 9.91 days) in comparison to other models.

8.2 Time Complexity Analysis of SMOWA-GA Algorithm

The SMOWA algorithm divides the whole population into multiple sub-populations depending upon the quality of the solutions. The SMOWA algorithm needs to perform a sorting operation to choose

Table 3. Values and Ranks of the objective function for Population 1, 2, 3, and 4

Run	Objective Function value				Ranks of Objective Function value			
	Population 1	Population 2	Population 3	Population 4	Population 1	Population 2	Population 3	Population 4
1	191751	202104	124869	191801	18	18	13	3
2	179910	190076	124512	180010	4	5	12	17
3	181777	197172	124992	181927	5	12	12	14
4	182301	185575	118590	182501	6	1	2	13
5	178160	193078	125340	178410	2	6	12	15
6	189667	197254	124042	189967	13	10	9	3
7	191813	190485	123198	192163	13	4	7	2
8	188939	193153	126845	189339	12	5	11	2
9	177806	202747	125063	178256	1	11	9	12
10	184070	187452	123034	184570	4	3	6	8
11	187755	193501	117906	188305	7	4	1	4
12	187330	185581	119118	187930	6	1	1	4
13	180921	201448	120884	181571	2	7	2	7
14	184775	192391	124193	185475	3	2	4	5
15	179467	194967	126773	180217	1	3	4	6
16	188045	194274	119821	188845	3	2	1	3
17	182293	198663	121640	183143	1	3	1	4
18	188205	203000	123731	189105	2	3	1	2
19	193213	185626	128940	194163	2	1	2	1
20	186451	197420	128573	187451	1	1	1	1

Table 4. The p-value calculation for Population 1, 2, 3, and 4

Parameters	Population 1	Population 2	Population 3	Population 4
count	20	20	20	20
Rank-sum	106	102	111	126
α	0.05	0.05	0.05	0.05
W	106	NA	NA	NA
W'	NA	102	NA	NA
W''	NA	NA	111	126
median	185613	193888	124118	186463
Variance	22523475.5	32578750.03	9870900	23088878.16
Standard deviation	4746	5708	3142	4805.088777
p-value	0	1.0149E-253	0	0

a better solution. The time complexity of SMOWA is $O(n \log n)$ where n is the no. of population. The complexity of GA is determined by the time complexity of different genetic operators' implementations, length of genes, population size, and, of course, the time complexity of the objective function. In this research paper one-point mutation, one-point crossover, stochastic selection operator has been implemented. The time complexity of the objective function is linear. So, the time complexity of the GA can be written as:

$G = \text{no. of generation}$

$L = \text{length of gene}$

$n = \text{no. of population}$

The crossover operator takes $O(nL)$.

The mutation operator takes $O(nL)$.

The stochastic selection operator needs to sort the population, so it takes $O(n \log n)$.

The objective function takes $O(n)$.

The overall complexity of GA can be obtained as:

$$O\left(G \cdot (nL + nL + n \log n + n)\right)$$

$$O(G \cdot nL)$$

So, the overall complexity of SMOWA-GA can be written as:

$$O(n \log n + G \cdot nL)$$

$$O(G \cdot nL)$$

8.3 Execution Time of SMOWA-GA Algorithm

The same populations as in Table 3 were evaluated, and the algorithm was run 20 times for each population and the execution time for each population is reported in Table 5. According to the statistical data, the p-value of Table 4, it can be said that Population 2 has higher significance than Population 1, Population 3, and Population 4, and the same thing is also reflected in the average execution time (0.005175 milli sec.) for Population 2 which is lower than the others.

9. CONCLUSION

The main aim of this paper is to prolong the lifetime of the network by minimizing the energy consumption of WSN. Various node deployment approaches have been used to evaluate the influence on the network's energy requirements. The multi-objective function has been used to address two different types of propagation models. A hybridized algorithm, SMOWA-GA, has been developed. The self-adaptivity capability of the algorithm makes it the best fit for the multi-objective problem. The statistical analysis, the Wilcoxon rank-sum test, of the experimental data, has been carried out

Table 5. Populations and their execution time

Run	Objective function value				Execution time (in milli sec.)			
	Population 1	Population 2	Population 3	Population 4	Population 1	Population 2	Population 3	Population 4
1	191751	202104	124869	191801	0.006	0.0053	0.0055	0.00610
2	179910	190076	124512	180010	0.0059	0.005	0.0056	0.00610
3	181777	197172	124992	181927	0.0055	0.0052	0.0056	0.00560
4	182301	185575	118590	182501	0.0057	0.0055	0.0055	0.00590
5	178160	193078	125340	178410	0.0053	0.0051	0.0054	0.00540
6	189667	197254	124042	189967	0.0055	0.0054	0.0057	0.00570
7	191813	190485	123198	192163	0.0056	0.0052	0.0055	0.00590
8	188939	193153	126845	189339	0.006	0.005	0.0055	0.00640
9	177806	202747	125063	178256	0.0057	0.005	0.0054	0.00600
10	184070	187452	123034	184570	0.0058	0.0051	0.0056	0.00620
11	187755	193501	117906	188305	0.0056	0.005	0.0054	0.00590
12	187330	185581	119118	187930	0.006	0.0053	0.0057	0.00640
13	180921	201448	120884	181571	0.0052	0.0052	0.0054	0.00530
14	184775	192391	124193	185475	0.0055	0.0055	0.0056	0.00570
15	179467	194967	126773	180217	0.0059	0.0051	0.006	0.00600
16	188045	194274	119821	188845	0.0058	0.005	0.0057	0.00600
17	182293	198663	121640	183143	0.0054	0.0052	0.0058	0.00550
18	188205	203000	123731	189105	0.0055	0.0051	0.006	0.00570
19	193213	185626	128940	194163	0.0059	0.005	0.0053	0.00620
20	186451	197420	128573	187451	0.0057	0.0053	0.0058	0.00610
					0.005675	0.005175	0.00560	0.00591
					Average Time	Average Time	Average Time	Average Time

to determine the significance of the population used in the experiment. The study compares the experimental performance of the proposed algorithm. According to the current literature (Banerjee et al. 2021b), the SMOWA-GA (using random deployment) has a lifetime improvement of 48.66 percent, the SMOWA-GA (using U pattern deployment) has a lifetime improvement of 56.56 percent, and the GA has a lifetime improvement of 32.54 percent.

In this hybrid SMOWA-GA algorithm, the accurateness of the solution depends on two factors: better selection of the quality population and better selection of different rate parameters (crossover rate and mutation rate) of GA. The self-adaptive multi-objective weighted approach method is responsible for better population selection, and the robustness of GA is dependent on the right selection of rate parameters. The trial-and-error strategy has been used in this study to determine the higher quality population as well as the value of rate parameters. Therefore the “trial-and-error strategy” is the limitation of this algorithm.

For further research, one can modify the proposed approach using advanced segregation (SMOWA), selection operators, and advanced termination criterion of the SMOWA-GA

algorithm. There are also many scopes to improve the optimization operators of the used optimization technique. In this research, this unique hybridized approach has been used to solve the minimization problem. This approach can also be applied to solve some maximization problems like area maximization of WSN.

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Sudip Kumar De is an Assistant Professor in the Department of Information Technology, Asansol Engineering College, West Bengal, India. He did his M.Tech in Information Technology from West Bengal University of Technology, India, in 2008. He also received Gold Medal in M.Tech. His research interests include topics in Wireless Sensor Network, Metaheuristic algorithms, Optimization techniques, Machine learning, and Geographical Information systems.

Avishek Banerjee is holding the position of Assistant Professor at Asansol Engineering College, Asansol, India. Dr. Banerjee earned his Ph.D. in Engineering at Jadavpur University, India in 2019. He received the EU-sponsored "Erasmus Mundus" scholarship at the University of Gheorghe Asachi, Iasi, Romania for 23 months of mobility. Earlier, he completed his M.Tech. (in Information Technology) from Calcutta University, India in 2007. He completed B.Tech. (in Information Technology) from the Vidyasagar University, India in 2007. He worked with different hybridization techniques of evolutionary algorithms to develop different hybrid Algorithms. Not only has he worked in several scientific fields such as Reliability Optimization and Evolutionary Algorithms, but he has also deep knowledge in engineering fields like Wireless Sensor Networks, Power Distribution Systems, and Natural Language Processing.

Koushik Majumder, Senior Member, IEEE Fellow, IETE Associate Professor Department of Computer Science & Engineering, Maulana Abul Kalam Azad University of Technology, West Bengal, has received his B.Tech and M.Tech degrees in Computer Science and Engineering and Information Technology in the year 2003 and 2005 with the university rank of 1st class 4th and 1st class 2nd respectively from University of Calcutta, Kolkata, India. He obtained his PhD(Engg.) degree in 2012 in the field of Mobile Ad hoc Networks from Jadavpur University. He has received National Certificates issued by the Ministry of Human Resource and Development, Government of India for securing high marks in Madhyamik, Higher Secondary and B.Sc(Hons) Examination. He had ranked 1st in the state of West Bengal in Science Talent Search Examination. Before joining the teaching profession he has worked in reputed international software organizations like Tata Consultancy Services and Cognizant Technology Solutions. He is presently working as an Associate Professor in the Department of Computer Science & Engineering in Maulana Abul Kalam Azad University of Technology, West Bengal. He is the Co-Chief Investigator of the "Information Security Education and Awareness (ISEA)" project phase-II under Ministry of Electronics and Information Technology (MeitY), Govt. of India. He has published several papers in International and National level journals and conferences and book chapters. He is a Senior Member, IEEE, Fellow of the Institution of Electronics and Telecommunication Engineers (IETE), Life Member of Computer Society of India (CSI), Member of the International Association of Engineers (IAENG), International Association of Computer Science and Information Technology (IACSIT) and Life Member of Advanced Computing and Communications Society (ACCS). He is presently serving as the editorial board member and reviewer of several international and national journals and conferences of repute.

Samiran Chattopadhyay obtained his B Tech and M Tech degrees in 1987 and 1989 respectively from the Department of Computer Science and Engineering, IIT Kharagpur. He obtained his Ph.D. degree from the Department of Computer Science and Engineering, Jadavpur University in 1993. He served as a faculty member in the Jadavpur University for more than 30 years. Dr. Chattopadhyay has more than two decades of experience serving reputed Industry houses. Currently, Dr. Chattopadhyay is a visiting fellow of the University of Northumbria, Newcastle upon Tyne UK. Dr. Chattopadhyay has published about 180 technical papers in international journals and conferences in the areas of Wireless Networks, Network Security, Machine learning applications. He has co-authored and edited more than 10 books His current research interests include Network Security, Machine learning, Wireless network, and Pervasive computing.