EAI Endorsed Transactions
on Internet of Things
Research Article EAI.EU

Binary Monkey-King Evolutionary Algorithm for single objective target based WSN

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Abstract

INTRODUCTION: Target based WSN faces coverage issue in which many targets could not be efficiently covered by static deployed sensors.
OBJECTIVES: This paper covers the issue of coverage problems by deploying the sensors to cover all the targets with minimized sensors in number.
METHODS: This paper proposes a Binary based Monkey King Evolutionary Algorithm for solving target based WSN problem, the proposed model consist a Binary method for converting the continuous values into binary form to solve the choice of potential position to place the sensors.
RESULTS: The proposed algorithm is evaluated in a 50x50 grid and 100x100 grid to track the performance and the performance of the proposed is compared with GA and PSO.
CONCLUSION: This paper utilized the MKE algorithm for improving the efficiency of the target coverage problem in WSN. It mainly focused on a single objective-based solution providing for small scale problems. From the simulation results, it is provided that the proposed MKE algorithm obtained 1.86 % of the F-value, which is higher than the other optimization algorithms such as GA and PSO.

Keywords: Single objective WSN, Genetic Algorithm, Particle Swarm Optimization, Monkey King Evolution Algorithm

Received on 01 July 2019, accepted on 23 July 2019, published on 29 July 2019

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doi: 10.4108/eai.29-7-2019.163970

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1. Introduction

Recently automation has been boomed drastically in our day-to-day lifestyle. Some of the real-life examples which include automation are driverless cars, houses without human security, etc. These automation techniques are highly used in various kinds of monitoring applications like monitoring, tracking, and measuring various environments. When comes to sensor networks the basic component used in the network is the sensor. Sensors can be deployed in any network, without changing the existing infrastructure can move, and communicate with one another using wireless communication mediums. It is also called Wireless Sensor Networks (WSN). The key point in WSN is coverage which means occupying the entire sensor field without any lack of performance. For the deployment strategy of WSN efficiently is still existing as a big task for the researchers. Many algorithms are proposed in either exact methods or as optimization techniques.

The exact method includes Dynamic Programming, Divide and Conquer Approach, etc. This algorithm works exhaustively. It generates and compares all the possible combinations of input values to obtain the best output. These kinds of exact algorithms are highly suitable for small scale problems or problems with less dimensional data. But for large scale problems, the time complexity of finding the best solution increases exponentially. Then comes a heuristic approach which is a problem-dependent method. These methods skip the exhaustive search by imposing a greedy approach or a random approach manner. But these algorithms often lead to stuck into local optimal solutions. The invention of Evolutionary algorithms has become a breakthrough in the domain of combinatorial problems. These algorithms are not problem-dependent. The inspiration for evolutionary algorithms comes from nature. The first proposed algorithm in evolutionary computing is a Genetic Algorithm [9] inspired by the human reproduction process. Later many algorithms have been proposed and some of them are ACO [8], PSO [7], etc. [14-21].

WSN deployment problem is one such combinatorial optimization problem where so many combinations of solutions are available. Achieving an efficient solution from those available solutions are pretty easier when it gets worked out with EA. Already many EA algorithms have been used to address the same issue of WSN but still, the researchers find scope in reaching the optimal solution in this domain. This paper concentrates on making a detailed survey of Evolutionary algorithms that solves a different kind of WSN issues and proposes a Binary Monkey King Evolution Algorithm for solving a single objective WSN deployment problem. The survey includes the objective of the paper, its constraints, the algorithm they propose and how it has been mapped into the WSN problem, the modifications made in a base algorithm, the need for modification, compared algorithms, parameters used and performance measures considered to evaluate the proposed algorithm.

The rest of the paper has been organized as follows: Section 2 presents the literature survey which composes of the evolutionary algorithms that are proposed in recent timings and section 3 follows with the explanation of some of the recent algorithms along with a brief mathematical notation. In section 4 the results were presented and a comparison has been made on the performance of the listed algorithm. Section 5 concludes the work and discuss future work.

2. Review of Related Literature

Suneet Kumar Gupta, et al. [1] presented a paper, Genetic algorithm approach for k-coverage and m-connected node placement in target-based wireless sensor networks. The objective of the paper includes coverage and connectivity in WSN for forwarding the data towards Base Station from each target with sensor nodes in between targets and base stations. The base algorithm they used to optimize the given scenario is a Genetic Algorithm. The way that the author mapped the algorithm with the problem is as follows: The sensor nodes of WSN are considered as genes in the Genetic Algorithm and a complete solution is considered as a chromosome. Each gene will be represented binary. If the potential node is placed in a potential position, then that gene will be considered as 1 else 0. The author represented the genetic algorithm in a binary format algorithm which helps to solve the problem using the proposed algorithm. The need for this modification is for efficiently handling the solutions without further offspring repair at the end of the iteration. The proposed algorithm has been compared with the Conventional GA, GREEDY Approach, and the algorithm proposed by Mini et al.[10]. The parameters used in the proposed algorithm include Total no. of target points, potential positions, communication range, population size, and Mutation rate. The comparison factors include potential positions of the sensor nodes and coverage area which is convincible by the placed node positions.

Mina Khalesian, et al. [2] proposed a paper Wireless sensors deployment optimization using a constrained Pareto-based multi-objective evolutionary approach. This paper addresses the coverage and efficiency in energy consumption of WSN concerning multiple constraints. The secondary objective comes with the Connectivity between sensor nodes. They resolved the issues with the evolutionary-based Genetic Algorithm. The authors mapped the genetic algorithm with their objectives in the following manner. The location of sensor nodes is represented in the form of genes. The binary representation of the genetic algorithm is handled here. Active sensor node locations are considered as 1 else 0. They proposed 2 types of crossover to make new offspring namely CrOv1 and CrOv2.These Crossover Operations incorporate not only the positions of their parents but also their geometric and topology characteristics. The proposed algorithm has been compared with NSGA-II and the results show remarkable improvements. The parameters they used are Generations, pop size, crossover rate, and mutation rate. The performance measures that are used to compare this proposed with the existing NSGA-II are NDS-Metric, C-Metric, Diversity Metric, HV-Metric, GD-Metric, Computation time.

Xuemei Sun, et al. [3] proposed a paper on Optimization deployment of wireless sensor networks based on culture–ant colony algorithm. The objectives they framed: To deploy sensor nodes to cover all monitored points. The constraints include Guaranteed coverage and connectivity between sensor nodes. A hybrid of culture algorithm and ant colony algorithm has been combined and proposed as the Culture-Ant colony algorithm. Mapping process of an existing problem with the proposed algorithm: Culture algorithm gives the population building solution to an ant colony system. The location of sensor nodes to cover the entire grid is represented as a complete solution of an ant. After population generation by ant, a set of belief space will be created by culture algorithm. The belief space improves the solutions to the optimal range with the help of the ant system. The modifications made in the proposed algorithm include the Hybrid of Ant colony and culture algorithm, incorporating the Greedy approach. The need for this modification is to efficiently build the population constructively. The greedy approach influences the greedy method in the absence of heuristic information. the proposed algorithm has been compared with Easidesign Algorithm [11] and ACO-TCAT. Parameters used in the proposed algorithm are pop size, pheromone rate, belief space level, threshold level, heuristic information rate. The proposed algorithm has been compared with the existing algorithms in the form of Optimal capacity analysis, Speed analysis, and stability analysis.

Mohammed Abo-Zahhad, et al. [4] presented a paper on centralized immune-Voronoi deployment algorithm for coverage maximization and energy conservation in mobile wireless sensor networks. The objectives of the paper include an efficient deployment of sensor nodes to cover maximum targets and minimize the total number of sensor nodes. The constraints plotted for achieving the objective are covering all target nodes. The evolutionary algorithm they used for addressing the issue is the Centralized Immune-Voronoi deployment Algorithm. The proposed algorithm has been mapped with the problem as follows: The position of sensor nodes is given as input to the immune optimization algorithm for efficient placement. To achieve the objective two phases are carried out for achieving maximum coverage and minimum usage of sensor nodes. Two kinds of the process are simulated and handled, they are Binary and Probabilistic Model. The probabilistic model creates a realistic environment that includes the mean error. The proposed CIVDA has been compared with PSO_Voronoi and WSNPSOcon.

Vishal Sharma, et al. [5] proposed a paper as A modified ant colony optimization algorithm (mACO) for energy-efficient wireless sensor networks. This objective has been framed is due to the limited battery power there exists a lack of using permanent cluster heads. To address this, a model has to be developed to prolong the network lifetime by keeping all nodes alive. The constraints which are to be satisfied are termed as connectivity between sensors and between the base station and sensors. The proposed algorithm is derived from the basic Ant Colony Optimization. The problem is mapped with the algorithm as follows: Each Ant represents a complete path to transfer the data which consists of sensor node positions. A threshold value is assigned to choose the path either by the indirect path model or free space model. The energy consumed by the indirect path will be higher when compared with the free space model. The modification incorporates an intra-spatial distance concerning battery power. The need for this modification is it tracks down the battery potential and switches the cluster head which keeps the network alive without any failure nodes. The proposed algorithm is compared with Conventional ACO. The parameters used in this algorithm are the overall energy consumed, the average amount of energy lost per signal. The algorithm has been evaluated with battery potential as its performance measure.

Md Azharuddin, et al. [6] published a paper as Particle swarm optimization for maximizing the lifetime of wireless sensor networks. The proposed algorithm has been framed is due to the hot spot problem, the nodes near to sink or base stations die either without power or fails due to bottle-neck sessions. Addressing a hot spot problem in a multi-hop communication leads to the availability of cluster-based WSN. The constraint is to make sure that the availability of all sensor nodes in a network to be alive. The proposed algorithm has the base of Particle Swarm Optimization. The problem of maximizing lifetime if WSN has been mapped into PSO in the following form: The gateways in a network are considered as components of a particle. Each particle consists set of nodes that are considered to be cluster heads (gateways) for forwarding packets towards the base station. Distribution of load throughout the network gateways has been done by re-routing the packets to neighbor gateways. The modification made in the proposed algorithm is incorporating a fault tolerance scheme. This is because of redirecting the packets to the next alive node which keeps the network alive. The proposed algorithm performance is compared with the existing algorithms like PSOK, GARS, GLBC, and GARA. The parameters taken for consideration are No. of sensor nodes, Initial energy of sensor nodes, Initial energy of gateways, communication range, packet size, message size. Comparative performance measure includes Network lifetime, total energy consumed, energy consumption per packet, dead gateways, Inactive sensor nodes, and standard deviation. Similar papers which address the problem of coverage in target-based WSN are in [22-25].

2.1 Limitation and Constraints

The limitation of the study is, NKE algorithm has been designed and tested only for a small scale network environment. Most of the earlier methods have focused on energy efficiency, not on throughput. But it Target coverage problem needs to satisfy the constraints like sensing region, a smaller number of sensors, more number of target nodes, and improved performance such as energy efficiency and throughput.

3. Proposed Work

In this section, a detailed introduction and formulation about the single-objective problem in WSN along with its constraints is given. Also, the general structure of the MKEA algorithm and also modified MKEA algorithm procedure are clearly stated with its mathematical formulation.

3.1 Problem Formulation

We assume a single objective problem in this paper. In conventional methods, to cover the target, a greater number of sensor nodes have been deployed. Even some of the targets have monitored by a set of sensors and gives a high accuracy result. This can be affordable for a small scale problem. For instance, if in case there exists a large scale problem then placing the sensors for each target seems to be an expensive one. So we frame an objective as to deploy a minimum number of sensor nodes to cover all targets. The localization of sensor nodes to achieve maximum coverage area with a minimum number of sensor nodes will be our objective in this paper. The mathematical formulation of our objective is as follows:

$$Maximize\ F = \frac{K}{L}$$

where K represents the total number of available potential positions of sensor nodes available in the network, L be the total number of localized sensor nodes and F is the ratio between available positions and deployed sensor nodes.

The objective of this paper comes with some constraints before achieving the maximized F and those includes,

(i) No targets should be leftover at the end of a complete solution.

(ii) Minimize the number of repeat coverage over the same node.

Given data for this formulated problem will be the total number of targets and their positions, maximum coverage region by a sensor node, position of sink node. The target positions will be given in a 2-dimensional co-ordinate format (x,y). The objective is to find the minimum number of nodes used to cover the targets and the position of those sensor nodes.

3.2 Monkey-King Evolution Algorithm

Z. Meng, et al.[12] proposed a novel inspired algorithm called memetic Monkey king evolutionary algorithm. This algorithm is inspired by a famous novel called Journey to the west which is a Chinese based novel. Apart from the stories described in the respective novel, the concept is derived from an intelligent mammal called Monkey king. The Monkey King is a single mammal as described. When a problem comes it becomes multiple small monkeys to solve the problem from different aspects. And when all the monkeys finish their respective jobs, the monkey with the optimal result will be considered as Monkey king for the next generation. This algorithm is an updated version of the Edd-Tide-Fish Algorithm [13]. Working on the Monkey-King evolution algorithm is described as follows.

3.3 The procedure of Monkey-King Evolutionary Algorithm:

Step 1: Define the proportion of Monkey-King particle (R) to participate with the existing population.

Step 2: Define the number of small monkeys which splits from one Monkey-King for exploitation (C x D)

Step 3: The exploitation can be performed as follows

$$X_{sm}(i) = \{x_1, x_2, \dots, x_j, \dots, x_D\}$$
$$x_j \rightarrow x_j \pm 0.2 * rand() * x_j, j \epsilon D$$

where D expresses the dimension of the given problem. X_{sm} represents a small monkeys' population that exists in C x D numbers. j represents the one small monkey particle among X_{sm}.

Step 4: Next-generation particle from the current generation of small monkeys X_{sm} can be obtained by

$$X_{MK,G+1} = opt\,\{X_{sm}(1), X_{sm}(2), .., X_{sm}(j), .., X_{sm}(CxD)\}$$

Step 5: For other particles of algorithms the searching process will be

$$X_{k,G+1} = X_{k,pbest} + F * rand() * (X_{gbest} - X_{k,G})$$

where k represents the particle. G represents the iteration number. Pbest represents the previous best of k^{th} particle. Gbest is the particle that holds the global optimal solution found so far from the start of iteration 1.

This algorithm extends its versions in 3 models. All the 3 versions are given in the paper [12]. The memetic of the Edd-Tide-Fish Algorithm shown improved results when compared to its inspired Edd-Tide-Fish Algorithm.

A. Mapping of MKEA – Single Objective WSN

The formulated problem can be mapped with Monkey King Evolution algorithm as follows:

BINARY MKEA-Single Objective WSN

Step1: Define the given positions of sensor nodes.

Step2: Define the population in binary format randomly.

$$I_d = \begin{cases} 1 & sensor\ node\ participate\ in\ evolution \\ 0 & sensor\ node\ does\ not\ participate \end{cases}$$

Step3: Define the proportion of Monkey King Particle (R) participate in this cycle

Step4: Define the number of small monkeys that can split from a single monkey (C x D)

Step5: do

Step6: The exploitation phase of the algorithm is as follows

$$X_{sm}(i) = \{x_1, x_2, \dots, x_j, \dots, x_D\}$$
$$x_j \rightarrow x_j \pm 0.2 * rand() * x_j, j \epsilon D$$

Step7: Define a threshold value ∂ for converting the values obtained from x_j.

Step8: Next generation individuals can opt from the current iteration as follows

$$X_{MK,G+1} = opt\ \{X_{sm}\ (1), X_{sm}\ (2), .., X_{sm}\ (j), .., X_{sm}\ (CxD)\}$$

Step9: The rest of the population can follow the equation with the same threshold value ∂ as above for binary representation of individuals.

$$X_{k,G+1}\ =\ X_{k,pbest} + F * rand() * (X_{gbest}\ -\ X_{k,G}\ )$$

Step10: while *(termination condition satisfies)*

3.4 Experimental results and Discussions

The experiment is carried out in two different scenarios like 50 x 50, and 100 x 100 sized network with a various number of target and sensor nodes deployed in the network. It helps to understand the efficiency of the MKE algorithm in terms of scalability. Computational time, several sensors used for target covering and F-Value are the parameters calculated to evaluate the performance. The results obtained using the MKE algorithm is compared with GA and PSO for evaluation.

The author performed an extensive set of experiments in MATLAB with a system configuration Core i5 Processor, 3,2 GHz, 8GB RAM and Windows 10 as the operating system. During the simulation systems, basic utility alone carried out to get a high accuracy over computational time results. There are 2 different scenarios carried out for testing the proposed algorithm. The 1st grid holds 50x50 square meter and the 2nd grid holds 100x100 square meter as their testbed. For 50x50 the base station is placed at 25x50 and for 2nd grid, it is 50x100. The available positions for sensor nodes are randomly generated after placing the targets in their respective places.

For execution process the parameters are set as follows:

Population size	100
Maximum iterations	500
R	3
C	10
Threshold Value (∂)	0.5

Performance Measures:

A. *Computational Time:* Total time taken for the algorithm to complete the given number of iterations. Here computational time is not concerning the best solution since the grid and positions of available sensors are randomly generation

$$Comp.Time\ = Time\ taken\ to\ compelete\ a\ cycle$$

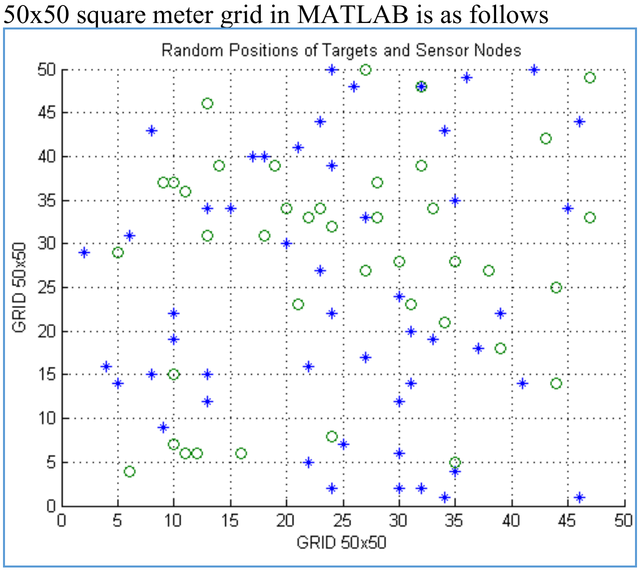
B. *No. of sensor nodes deployed:* The total number of sensor nodes that are deployed from the number of available potential positions of sensor nodes.

C. *F value:* F value is the ratio between the number of available positions to plot the sensor nodes and the total number of sensor nodes deployed at the end of the cycle.

$$F = \frac{K}{L}$$

where K is the total number of available positions to plot the sensors and L total number of deployed sensors.

The randomly generated targets and sensor nodes in a 50x50 square meter grid in MATLAB is as follows



o – Sensor Nodes * - Targets

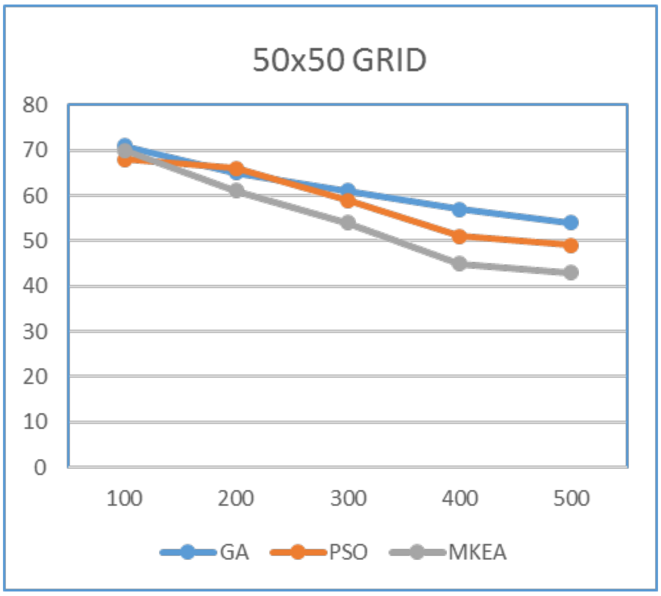
A total of 50 random generated targets and 40 sensor nodes are placed in this 50x50 Grid.

The computational time and F-value calculated using MKE, GA, and PSO for a 50 x 50 sized network is given in the following table. In terms of computational time, PSO obtained lesser time (5.14s) and the F-value MKE algorithm obtained the highest value as the best values. PSO has two different searching methods such as local search and global search which give the best optimal value. In terms of accuracy, the MKE algorithm obtained the highest F-Value (1.90) for 21 nodes deployed. This same simulation is done with the algorithms GA and PSO to compare the performance of the proposed algorithm. The results for 50x50 grid is tabulated below

	Comp. Time (s)	No. of Nodes Deployed	F-Value
GA	6.23	31	1.29
PSO	**5.14**	24	1.66
MKEA	5.22	**21**	**1.90**

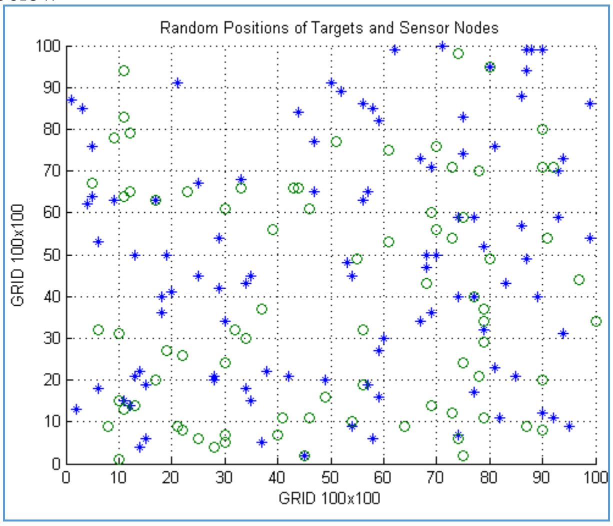
In the above table 1.1 results of GA, PSO and the proposed MKEA are compared in terms of Computational time, Number of nodes deployed at the end of the iteration and the F-value which is our objective of maximizing it. When comparing the computational time PSO seems to be converged faster since our proposed MKEA takes C times of exploitation process during each iteration. When comparing several nodes deployed and F-value, the proposed algorithm outstands when compared with other algorithms.

Representation of the total number of nodes deployed for every 100 iterations in a 50x50 grid in the form of a chart is given below.



The x axis represents the number of iterations and y axis represents total number of nodes deployed at those iterations. The figure shows the MKE algorithm obtained better results than the other existing approaches.

For 100x 100 grid the random simulated map is given below

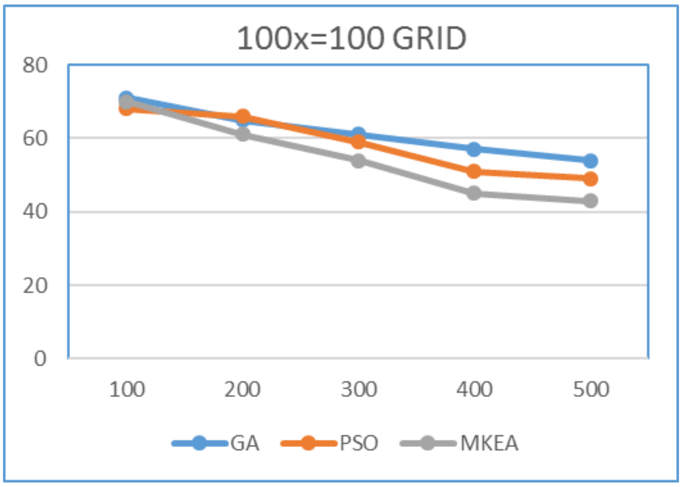


o – Sensor Nodes * - Targets

For instance, this same map is used to evaluate the compared GA and PSO simulation. This map holds a total of 100 targets and 80 sensors randomly planted in the 100x100 grid. Below tabulation holds the performance values of GA, PSO and MKEA algorithm. The computational time and F-value calculated using MKE, GA, and PSO for a 100 x 100 sized network is given in the following table. In terms of computational time, PSO obtained lesser time (7.32s) and the F-value MKE algorithm obtained the highest value as the best values. PSO has two different searching methods such as local search and global search which give the best optimal value. In terms of accuracy, the MKE algorithm obtained the highest F-Value (1.86), which is less than obtained for 50x50 network size.

	Comp. Time (s)	**No. of Nodes Deployed**	**F-Value**
GA	9.17	54	1.48
PSO	**7.32**	49	1.63
MKEA	8.01	**43**	**1.86**

The performance measure of the proposed algorithm has been evaluated in terms of computational time, no of nodes deployed and F-Value. The table indicates that the performance of the proposed algorithm outperforms.



The x-axis represents the number of iterations and the y-axis represents the total number of nodes deployed at those iterations.

Since the number of target and sensor nodes are generated randomly, the distance among the target nodes and the sensor nodes are different. The computational time and the F-value will not be constant, due to distance variation. Hence the number of simulations is repeated for a constant number of iterations and the results obtained.

The convergence ratio of the MKE algorithm is less than the GA and PSO for both network sizes.

To test the algorithm, the sensors are deployed in the open space to monitor the air pollutant level mixed in the air. Some of the sensors used to monitor the pollutants are, Shinyei PPD42 to sense Particulate Matter, MiCS-2714 Gas Sensor for sense NO2 level, MiSC-2614 Gas Sensor for sensing the Ozone level, and Keyes DHT11 Temperature and Humidity Sensor for temperature and humidity level mixed in the air. These kinds of sensors are deployed randomly in a particular area and the sensed data is verified. The set of sensors is deployed, localized, and obtain the sense of the target data using the MKE algorithm. Each sensor searches the appropriate gas based on their sensing power in the network environment. The amount of sensing data is depending on the MKE algorithm implemented where the sensors follow it.

Based on the amount of data sensed by the sensors within a time interval to verify the efficacy of the sensors. To evaluate the performance of the MKE algorithm the number of nodes deployed in the network area is changed and the amount of data is verified. The corresponding result is given in the following table. From the table, it is identified that the amount of data collection is directly proportional to the number of sensors.

Sr. No.	Number of nodes (including all kind of sensors)	Amount of data collected.
1	50	1.43GB
2	100	4.9GB
3	150	6.87GB
4	200	8.23GB
5	250	11.23GB

The proposed MKE algorithm outperforms the other optimization algorithms such as GA, and PSO. From the obtained results, it recommended that the MKE algorithm is highly suitable for solving target coverage problems in small scale based WSN. Some of the specific applications are air pollution calculation, a single view of a large building.

The proposed MKE algorithm is programmed in MATLAB software and the explained scenario is simulated. In each scenario like 50x50 and 100x100 sized network with a different number of targets and sensor nodes are deployed. In each scenario, the performance factors help to evaluate the MKE algorithm are computed and verified. From the obtained results the potential ability of the proposed approach is evaluated. From the results, it is identified that the proposed algorithm can fill the gap between theory and practice.

4. Conclusion

In this paper, a Modified Binary Monkey King Evolutionary Algorithm is proposed to address the target based Single Objective WSN problem. For the derivation of this single objective problem in WSN, a detailed survey has been taken which is presented in the literature survey section. The proposed work of deploying sensor nodes in minimal number to cover all the targets in a WSN has been simulated in MATLAB and results are tabulated. The tabulated results show that the proposed algorithm outperforms in terms of F-value when compared to GA and PSO.

Future work of this research may enhance towards achieving multi-objective target based WSN with any Multi-Objective Evolutionary Algorithm.

References

[1] Gupta, S. K., Kuila, P., & Jana, P. K. (2016). Genetic algorithm approach for k-coverage and m-connected node placement in target based wireless sensor networks. Computers & Electrical Engineering, 56, 544-556.

[2] Khalesian, M., & Delavar, M. R. (2016). Wireless sensors deployment optimization using a constrained Pareto-based multi-objective evolutionary approach. Engineering Applications of Artificial Intelligence, 53, 126-139.

[3] Sun, X., Zhang, Y., Ren, X., & Chen, K. (2015). Optimization deployment of wireless sensor networks based on culture–ant colony algorithm. Applied mathematics and computation, 250, 58-70.

[4] Azharuddin, M., & Jana, P. K. (2016). Particle swarm optimization for maximizing lifetime of wireless sensor networks. Computers & Electrical Engineering, 51, 26-42.

[5] Abo-Zahhad, M., Sabor, N., Sasaki, S., & Ahmed, S. M. (2016). A centralized immune-Voronoi deployment algorithm for coverage maximization and energy conservation in mobile wireless sensor networks. Information Fusion, 30, 36-51.

[6] Sharma, V., & Grover, A. (2016). A modified ant colony optimization algorithm (mACO) for energy efficient wireless sensor networks. Optik, 127(4), 2169-2172.

[7] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In Proceedings of ICNN'95-International Conference on Neural Networks (Vol. 4, pp. 1942-1948). IEEE.

[8] Colorni, A., Dorigo, M., & Maniezzo, V. (1991). Distributed Optimization by Ant Colonies, actes de la première conférence européenne sur la vie artificielle. In Elsevier Publishing (pp. 134-142).

[9] Holland, J. H. (1992). Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence. MIT press.

[10] Mini, S., Udgata, S. K., & Sabat, S. L. (2012). *M*-Connected Coverage Problem in Wireless Sensor Networks. ISRN Sensor Networks, 2012.

[11] Liu, X. (2012). Sensor deployment of wireless sensor networks based on ant colony optimization with three classes of ant transitions. IEEE Communications Letters, 16(10), 1604-1607.

[12] Meng, Z., & Pan, J. S. (2016). Monkey king evolution: a new memetic evolutionary algorithm and its application in vehicle fuel consumption optimization. Knowledge-Based Systems, 97, 144-157.
[13] Meng, Z., & Pan, J. S. (2015). A simple and accurate global optimizer for continuous spaces optimization. In Genetic and evolutionary computing (pp. 121-129). Springer, Cham.
[14] Ebrahimi, A., & Khamehchi, E. (2016). Sperm whale algorithm: an effective metaheuristic algorithm for production optimization problems. Journal of Natural Gas Science and Engineering, 29, 211-222.
[15] Muthiah-Nakarajan, V., & Noel, M. M. (2016). Galactic Swarm Optimization: A new global optimization metaheuristic inspired by galactic motion. Applied Soft Computing, 38, 771-787.
[16] Tang, D., Dong, S., Jiang, Y., Li, H., & Huang, Y. (2015). ITGO: Invasive tumor growth optimization algorithm. Applied Soft Computing, 36, 670-698.
[17] Hatamlou, A. (2013). Black hole: A new heuristic optimization approach for data clustering. Information sciences, 222, 175-184.
[18] Gandomi, A. H. (2014). Interior search algorithm (ISA): a novel approach for global optimization. ISA transactions, 53(4), 1168-1183.
[19] Taherdangkoo, M., Paziresh, M., Yazdi, M., & Bagheri, M. H. (2013). An efficient algorithm for function optimization: modified stem cells algorithm. Central European Journal of Engineering, 3(1), 36-50.
[20] Doğan, B., & Ölmez, T. (2015). A new metaheuristic for numerical function optimization: Vortex Search algorithm. Information Sciences, 293, 125-145.
[21] Eskandar, H., Sadollah, A., Bahreininejad, A., & Hamdi, M. (2012). Water cycle algorithm–A novel metaheuristic optimization method for solving constrained engineering optimization problems. Computers & Structures, 110, 151-166.
[22] Chen, D. R., Chen, L. C., Chen, M. Y., & Hsu, M. Y. (2019). A coverage-aware and energy-efficient protocol for the distributed wireless sensor networks. Computer Communications, 137, 15-31.
[23] Adasme, P. (2019). Optimal sub-tree scheduling for wireless sensor networks with partial coverage. Computer Standards & Interfaces, 61, 20-35.
[24] Kabakulak, B. (2019). Sensor and sink placement, scheduling and routing algorithms for connected coverage of wireless sensor networks. Ad Hoc Networks, 86, 83-102.
[25] Xu, Y., Ding, O., Qu, R., & Li, K. (2018). Hybrid multi-objective evolutionary algorithms based on decomposition for wireless sensor network coverage optimization. Applied Soft Computing, 68, 268-282.