International Journal on Perceptive and Cognitive Computing (IJPCC) Vol 11, Issue 2 (2025)
https://doi.org/10.31436/ijpcc.v11i2.603

# Implement Hybrid Algorithm to decrease localization error in Wireless Sensor Network

Maan Younus Al-fathi

Computer science of College of education and pure science, university of mosul, Mosul, Iraq.

*Corresponding author: dr.maan.y@uomosul.edu.iq

(Received: 24th June 2025; Accepted: 26th July, 2025; Published on-line: 30th July, 2025)

***Abstract***—The enormous technical development has resulted in the ubiquitous adoption wireless sensor networks (WSN) in many spheres of life, posing great obstacles, the most essential of which is location determining. There are three most well-known methods to handle these difficulties: Based on the K-means model (an algorithm for grouping data) the first method divided a data set. The second method is the PSO algorithm, which makes use of a group of elements known as a "swarm" randomly dispersed in a constrained area to arrive to the ideal answer. The third method is the genetic algorithm, which uses Darwinian perspective imitation of the work of nature to attain optimum. In order to decrease the localization error in this paper, a hybrid method was applied leveraging the advantages of the genetic algorithm and the swarm intelligence algorithm. Actually, this method was evaluated individually against the k-means method, the intelligent swarm algorithm, and the genetic algorithm. The novel method greatly lowered the localization error in wireless networks and obtained an average error of 28.56 m, the lowest among the three compared techniques. The performance of the suggested method was assessed by means of simulations adjusting numerous PSO and GA parameters. While the results of GA and PSO converge and one may move over the other, the experimental results revealed that the suggested algorithm is always the best and k-means is the lowest.

***Keywords***— sensor, genetic algorithm, Wireless sensor networks.

## I. Introduction

Technology that utilizes wireless sensor networks has gained widespread recognition as a result of the widespread implementation of applications such as the Internet of Things. Mobile sensor networks are utilized in a wide variety of applications, including battlefield surveillance, earthquake detection, and other safety or essential monitoring [1]. When it comes to wireless sensor networks (WSNs), localization is an important field of exploration that scientists can use and investigate. This is because localization plays an important part in WSNs. The WSNs, which are depicted in Figure 1, are utilized for the purpose of transferring the data that corresponds to the surrounding observations to the BS based system. The majority of the applications are associated with location awareness, which is the process of determining the location of a node, which can be either an unknown or a seen node. A refinement of the data that was obtained is performed using the position information of the node [2].

In some situations, it is not viable to perform canonical actions to identify individual sensor nodes. Localization is the process of estimating the node's position using current information.

Localization in Wireless Sensor Networks (WSNs) aims to deploy a sensor in a specified area of interest to its neighbours. Localization strategy is influenced by the distance estimating technique. Computer algorithms [3] help one to find suitable distance values. K-means and other computational intelligence methods such the Genetic Algorithm can find the optimal distance. Every approach is executed differently [4]. This work, however, applies and contrasts Swarm Intelligence-based approaches with K-Means and Genetic Algorithm (GA) using the recommended approach. Recent developments in localization and clustering show that K-Means, GA, and PSO could tackle challenging issues [5].

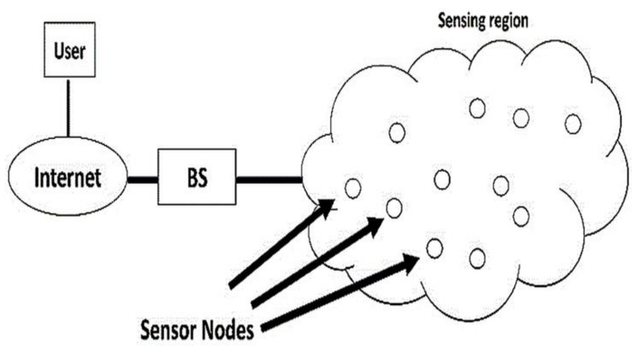


Fig. 1 WSN : Wireless Sensor Network

https://doi.org/10.31436/ijpcc.v11i2.603

Distinguished clustering technique K-Means divides data into K clusters and simultaneously reduces the variation within every cluster. Although it may be sensitive to the initial centroid, which could result in the development of local minima, the fact that it is so simple and efficient makes it a great choice for big datasets. Based on natural selection, genetic algorithms (GA) are useful for investigating vast and complicated search spaces; nevertheless, if improperly tuned, they can be computationally costly and show early convergence tendency. Similarly, PSO, which is based on social behaviour in nature, has a simple implementation and is successful in a range of optimization tasks, but it also meets the problem of early convergence in complex scenarios [6]. Although these algorithms have great value, it is imperative to fully understand their shortcomings if one is to create more solid solutions. On this research is to address these deficiencies by presenting an exhaustive analysis of hybrid optimization methods that are utilized in the process of wireless sensor network localization. We explore the complexity of localization methods including evolutionary algorithms, PSO algorithms, and meta-algorithmic approaches with special focus on how these methods may be used to reach accurate and efficient localization inside wireless sensor networks. [7].

The purpose of this study, is to implement and analyze the performance of approaches based on swarm intelligence in comparison with basic techniques such as K-Means and Genetic Algorithm (GA), and then compare those techniques with the algorithm that has been proposed.

## II. Literature review

This section synthesizes recent surveys from review studies to highlight localization error's current issues. It also reveals its future. Many scholars have researched wireless sensor network localization error reduction. To demonstrate the new algorithm's efficiency, we'll compare its research to previous investigations. [8] Wireless communication's basic features and the changeable network environment make WSN localization difficult [9]. Optimization methods find the ideal node placements to minimize localization errors or maximize network connection [10].

Recently, swarm intelligence approaches have gained popularity for solving a variety of optimization challenges. K-Means, PSO, GA, and hybrid algorithms can improve WSN localization [11]. In [12-14], K-Means localizes nodes by proximity. Simple and computationally efficient, K-Means is ideal for large networks. While minimizing localization mistake, its centroids sensitivity may lead to poor grouping and more errors. K-Means assumes spherical clusters, although WSNs with unequal nodes may not. WSNs localize using PSO, a population-based optimization method influenced by bird or fish social behavior. PSO's main value is finding optimal solutions in huge spaces without gradient information. It aids dynamic localization and ongoing improvement. Early PSO convergence, especially in high-dimensional search spaces, reduces solution quality and localization accuracy [5]. Modifying inertia weight and particle velocity lessens this but complicates algorithms.Genetic algorithms are widely used to optimize WSN localization [4]. GAs cross, mutate, and choose solutions like natural selection. GAs consistently solve complex, multimodal optimization problems, making them suitable for WSN localization with huge, nonlinear solution spaces. GAs require a lot of computational resources for repetitive search, which may slow processing. Untuned GAs may prematurely converge, resulting in unsatisfactory solutions and excessive localization error [15].

K-Means, PSO, and GA complicate WSN localization mistake, with pros and cons. K-Means setup-dependent but computationally efficient. PSO searches broadly but may converge early. Although computationally expensive, GA can solve difficult problems. PSOs and methods reduce localization error, especially in big WSNs. As the field develops PSO methods could help to limitation localization error. In this study have implemented a new hybrid algorithm formulating the combined advantage of the local modification options of GA and global search ability of PSO. The performance analysis results according to simulations reveal that the hybrid approach achieves higher performance on localization error reduction in WSNs if compared with standalone PSO, GA, and K-Means methods (28.56 m on average).

## III. K-mean

Data can be categorized into clusters by a technique known as clustering, which organizes the data based on the level of similarity among various categories [16]. Recent advancements enhance the reliability of localization by integrating K-means with fault-tolerant systems to identify and eliminate defective nodes [17]. For the method to be effective, it must initially create a cluster by arbitrarily selecting specific central locations, referred to as centroids, from the pool of available sites. Upon completion, each data point is allocated to the centroid nearest to it. Once each point is allocated to a cluster, the centroids are updated by computing the average position of the points inside each cluster.

This procedure is reiterated until every point has been allocated to a cluster. It is necessary to repeat this process until the centroids stabilize and clusters are formed to attain the desired outcomes. Clustering is a method that partitions data points into clusters, ensuring that the points inside each cluster are similar to one another. The objective of

https://doi.org/10.31436/ijpcc.v11i2.603

clustering is to attain this condition. The combination of K-means with multi-layer methodologies improves the identification of data patterns in multi-target localization contexts [18].

## IV. Evolutionally techniques in WSN

### A. Swarm intelligence (PSO)

PSO algorithm uses a swarm-based search procedure, where each particle represents a potential solution in D-dimensional space. Each particle can remember the optimal position of the swarm, its own, and its velocity. Particle information is combined in each generation to change velocity and compute the particle's new position. Particles constantly adjust their states in multi-dimensional search space until reaching balance or optimality, or exceeding calculating constraints. Unique connections between problem space dimensions are established using objective functions. There is ample empirical evidence that this algorithm is an efficient optimization tool. By utilizing decentralized algorithms that draw inspiration from nature, PSO can enhance the performance of wireless sensor networks (WSNs). PSO optimizes network characteristics by modifying particle velocities and locations depending on individual and collective experiences using equations 1 and 2:

$$V\_I(T+1) = W * V\_I(T) + C1 * R1 * (P\_BEST - X\_I(T)) + C2 * R2 * (G\_BEST - X\_I(T)) \quad \ldots\ldots(1)$$

$$X\_I(T+1) = X\_I(T) + V\_I(T+1) \quad \ldots\ldots (2)$$

Particle i's velocity and position are v_i and x_i. w is the inertia weight, c1 and c2 are acceleration coefficients, r1 and r2 are arbitrary values between 0 and 1, and p_best and g_best are the particle and swarm's best-known positions. These methods boost WSN energy efficiency, data routing, and fault tolerance. Recently, swarm intelligence technologies have optimized WSN performance[19]. When it comes to wireless sensor networks (WSNs), PSO has been utilized to maximize node placement approaches, hence boosting coverage and connectivity [20].

### B. Genetic algorithms

GAs in wireless sensor networks help to maximize energy economy, coverage, and endurance. Crossover, mutation and selection constitute the three primary operators for modelling natural selection [21].

To raise their genetic transmission, the selection operator selects from the population people with superior fitness degrees using a fitness function. Higher residual energy in wireless sensor network cluster heads helps to maximize energy use.

In crossover, two parents' genetic material is combined to produce children with variation. Between two wireless sensor network topologies, the exchange of routing path segments could probe new routing techniques[22].

By randomly changing genes, mutation preserves genetic variety and avoids convergence. In a wireless sensor network, this could mean shifting sensor nodes at will to increase coverage. Nodes must be positioned deliberately for best coverage of a wireless sensor network .. Each chromosome signifies a possible configuration of nodes. The fitness function assesses the coverage area of each configuration. The genetic algorithm (GA) enhances node placements iteratively through selection, crossover, and mutation to attain optimal coverage.

## V. Proposal hybrid algorithm

Through the utilization of the advantages offered by both Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), the hybrid algorithm that has been suggested is able to minimize the amount of localization error that occurs in wireless sensor networks (WSNs) in an ideal manner, as shown in Figure 2. PSO's swarm-based search initially performs an efficient exploration of the solution space, hence locating promising node sites. After that, genetic algorithms, with a more refined population size, improve solutions by employing factors such as selection, crossover, and mutation. As the initial population for GA, the best solution that was obtained by PSO is provided. This ensures that GA will converge more quickly and with more precision. For the purpose of reducing the number of localization error, this adaptive hybridization works better than PSO, GA, and K-Means clustering.

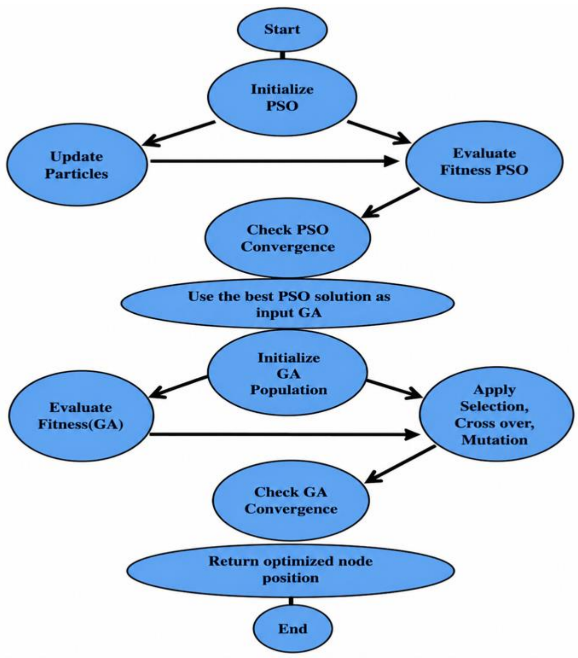


Fig. 2 Flowchart of the Hybrid Algorithm

https://doi.org/10.31436/ijpcc.v11i2.603

The hybrid algorithm's flowchart is found in figure 2. It graphically shows the sequence whereby PSO first searches the search space and finds an optimal solution, which is subsequently passed as an initial population to GA for additional improvement via selection, crossover, and mutation. Plotting the cumulative distribution function (CDF) of localization error helps one to evaluate several techniques [23–24]. The equation (3) [25]

$$F(x)=P(E\leq x) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(3)$$

It is the Cumulative Distribution Function (CDF) of the localization error E. It represents the probability that the localization error is less than or equal to a given value x. Explanation of terms are :

- F(x): The CDF, which gives the probability that the random variable E (localization error) is less than or equal to x.
- P(E≤x): The probability that the error does not exceed x, meaning the fraction of observations (or samples) where the error is at most x.
- E: A random variable representing the localization error.
- x: A threshold value for localization error.

interpretation of mathematical concepts a continuous random variable's standard deviation (CDF) E can be defined using equation (4) as follows:

$$F(x) = \int_{-\infty}^{x} f(t)dt \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(4)$$

f(t) is the Probability Density Function (PDF) of E. The integral sums up all probabilities from −∞ to x, ensuring that F(x) always increases as x increases. *For discrete data, the CDF is computed as equation (5):*

$$f(x) = \frac{Numberof\ value\ E\leq x}{Total\ number\ of\ values}\ldots\ldots\ldots\ldots.(5)$$

It is Effective for Analyzing Localization Errors Imagine a network of one hundred sensor nodes, each of which has its own unique localization error. Assuming fifty nodes have errors of five meters or less, the following can be said:

$$F(5)\frac{50}{10} = 0.5$$

This means 50% of the nodes have localization errors ≤ 5 meters. If 80 nodes have errors less than or equal to 7 meters, then:

$$F(6)\frac{80}{100} = 0.8$$

Meaning 80% of the nodes had localization erorr less than seven meters. Assume for ten nodes we have localization error data:E=[2.5,3.0,4.1,4.2,5.0,5.5,6.3,7.1,8.0,9.5].In order to calculate F(6):Count the mistakes ≤6; from these are values: 2.5,3.0,4.1,4.2,5.0,5.5 => 6 numbers. Where is a F(6) = 6/10 = 0.6 are indicates that 60% of nodes exhibit localization errors of 6 meters or less. The CDF is advantageous in WSN optimization due to the following reasons [26]:

Evaluates the effectiveness of optimization methods (e.g., PSO, GA) in reducing localization error.

- Comparison: PSO achieves more accurate localization if its CDF is steeper than GA.
- Assists in decision-making by assessing the number of nodes within acceptable error limits for localization.

## VI. Computational Complexity

Computational complexity is the quantity of steps an algorithm takes, based on the size of an input. For example, in PSO, GA, Hybrid, different complexity parameters as number of iterations, population size, and dimensions are taken into account. PSO is a research approach which iteratively evolved by adjusting the position and the velocity of those particles. Its time complexity is determined by these factors and can be formulated by concrete time complexity equations without using terms of numbers of solutions, iterations, as well as dimensions. Time Complexity of PSO = O(N×M×D) Where N= no. of particles (swarm size), M=(No. of iteration) and D=(No. of dimension (Optimize Variable)). The complexity is linear to the number of particles, and to the number of iterations, and to the number of dimensions, because a particle's fitness has to be evaluated for every dimension based on every iteration. GA works by selection, crossover and mutation of a population of candidate solutions. The Computational complexity of genetic algorithms are:

Time Complexity of GA=O(P×G×(N×D)) . Where:P= (Population size),G= (Number of generations),N= (Number of individuals (in the population)) and D= (Number of variables (dimensions) in each individual (chromosome)). The complexity involves processing the entire population for each generation, where each individual's fitness evaluation depends on the number of variables. The hybrid algorithm combines PSO and GA by leveraging the global search capability of PSO and the local search refinement of GA. The total computational complexity of the hybrid approach is: Time Complexity of Hybrid Algorithm =O(NPSO×MPSO×D)+O(PGA×GGA×(NGA×D)) Where: NPSO, MPSO, and D refer to the PSO parameters. PGA, GGA, and NGA refer to the GA parameters. The PSO hybrid version initially runs PSO and after that, to apply the hybrid algorithm, (5) is utilized, where the fitness value of each particle is evaluated for MPSO iterations. Then the best one

https://doi.org/10.31436/ijpcc.v11i2.603

in PSO is sent to GA, and GA evolves it GGA generations. Thus, the time complexity is the addition of the time complexities of PSO and GA.

Memory footprint is the ram occupied by variables and intermediary results. This memory contains information for the particles, the population and variables such as best solutions and velocities of PSO, GA and Hybrid algorithms. The memory requirement of PSO can be assessed as: Memory Footprint of PSO = O(N×D)+O(N×D)+O(N×D)+O(D) where : N = Number of particles and D = Number of dimensions (variables). Each particle stores its position and velocity, requiring N×D memory for positions and velocities.Additionally, the algorithm stores the best position for each particle and the global best position, which requires N×D memory for personal bests and D memory for the global best. The memory footprint of GA can be expressed as: Memory Footprint of GA = O(P×D)+O(P)+O(P×D) where : P = Population size and D = Number of dimensions (variables). The population consists of P individuals, and each individual is a chromosome of size D, so O(P×D) memory is needed. Additionally, the fitness values for each individual require O(P) memory.Temporary storage for crossover and mutation also requires O(P×D).finally, the memory footprint of the Hybrid Algorithm is the sum of the memory required for PSO and GA: Memory Footprint of Hybrid Algorithm= O(NPSO×D)+O(NPSO×D)+O(NPSO×D)+O(D)+O(PGA×D)+O( PGA)+O(PGA×D). Memory Footprint of Hybrid Algorithm=O(NPSO×D)+O(NPSO×D)+O(NPSO×D)+O(D)+O( PGA×D)+O(PGA)+O(PGA×D) Where: NPSO, MPSO, and D refer to the PSO parameters. PGA, GGA, and D refer to the GA parameters. These are the equations that explain the computational complexity and memory requirements of the PSO, GA and Hybrid algorithms, and they should provide a very good idea of the kind of resources you need to use each of them. Furthermore, MATLAB simulation results were used to perform a comparison in performance. The results demonstrate that the introduced hybrid approach exhibits a small mean localization error (28.56 m) which outperforms individual PSO (32.85 m), GA (32.39 m), and K-Means (52.58 m) methods. These results are presented in Figures 4 and 5 and discussed in the Results and Discussion.

## VII. Result and Discussion

In order to carry out simulations, an Intel Core i-5 computing machine was utilized, and the Network Simulator (MATLAB) was utilized for the coding process. When there are no values that are lower than the smallest mistake, a CDF plot begins at zero and climbs to one. This occurs when all of the values have been taken into account. If the CDF curve is steeper, then the mistakes will be more frequently grouped around lower values, which will result in improved accuracy. Flatter curves imply less dependability of localization and more scattered inaccuracy. Making decisions by evaluating the number of nodes inside error boundaries helps one choose the optimum localization method. A statistical measure of a localization error E below a given threshold x is the CDF, F(x)=P(E≤x). This article evaluates optimization strategies by measuring the statistical correctness of localization in WSNs. A steeper CDF denotes better localization accuracy; a slow CDF denotes generally large errors.

```
%% Parameters
num_nodes = 100;    % Total sensor nodes
num_heads = 20;     % Cluster heads
area_size = 100;    % 100x100 meters
max_iter = 100;     % Maximum number of iterations for PSO and GA
swarm_size = 300;   % Number of particles in PSO
ga_population = 50; % Population size for GA
kmeans_iter = 100;  % K-Means iterations

%% Generate Node Positions
rng(42);        % For reproducibility
nodes = area_size * rand(num_nodes, 2);   % Random positions for sensor nodes
head_indices = randperm(num_nodes, num_heads);  % Randomly select cluster heads
cluster_heads = nodes(head_indices, :);   % Cluster heads positions

%% PSO Parameters
w = 0.5;    % Inertia weight
c1 = 1.5;   % Cognitive coefficient
c2 = 1.5;   % Social coefficient
dim = 2;    % Dimensionality (2D space)

% Initialize PSO particles
particles_pos = area_size * rand(swarm_size, num_nodes, dim);  % Random initial positions
particles_vel = zeros(swarm_size, num_nodes, dim);      % Zero initial velocities
personal_best_pos = particles_pos;          % Personal best positions
personal_best_error = inf(swarm_size, 1);   % Personal best errors
global_best_pos = zeros(1, num_nodes, dim);   % Global best position
global_best_error = inf;   % Global best error

%% PSO Optimization Loop
```

Fig. 3 Parameters of MATLAB program PSO, GA, k-mean and Hybrid algorithm

These techniques degrease the localization error, hence increasing network dependability and efficiency. Combining the advantages of both optimization approaches helps the hybrid algorithm to increase the localization accuracy of Wireless Sensor Networks. PSO starts off quickly looking for the best location. Through selection, crossover, and mutation, GA polishes the response. Better than alone PSO, GA, and K-Means clustering this hybrid approach decrease localization error. The Euclidean distance equation (7) is used to determine the localization error, which is as follows:

$$Ei = \sqrt{(x_{true,i} - x_{est,i})^2 + (y - y_{est,i})^2} \ldots\ldots\ldots (7)$$

where Ei is the localization error of node i, ($x_{true,i}$,$y_{true,i}$) are the actual coordinates of the node, and ($x_{est,i}$,$y_{est,i}$) are the predicted positions of the node, where Ei is the localization error of node i, ($x_{true,i}$,$y_{true,i}$) are the actual coordinates of the node, and ($x_{est,i}$,$y_{est,i}$) are the predicted positions of the node.

This is demonstrated by the cumulative probability distribution, the total number of target nodes in the area is fix as 100 and 20 as cluster head for this simulations. the density of anchor nodes (per m2) and value for different parameters of simulation is given in figure 3 that first page of MATLAB program.

In Figure 4 is shown demonstrates that the hybrid technique produces lower error than other methods. Matlab was utilized in order to carry out the simulation study as well as the performance analysis of the proposed scheme. For the purpose of simulation, a sensor network consisting of static target and anchor nodes would be installed in an area measuring 100 meters by 100 meters. Randomly generated (x,y) coordinates within the boundary are used to represent the positions of the nodes (see figure 4 for further information concerning this).

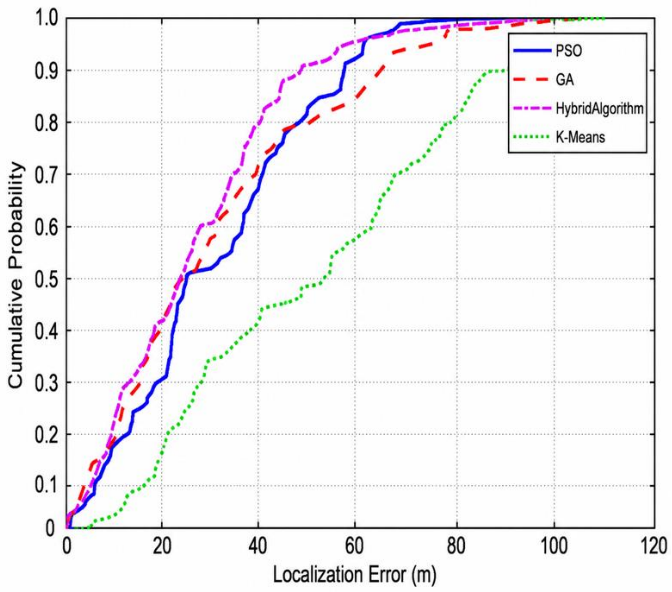


Fig. 4 Comparison among PSO, GA, K-mean and hybrid algorithm

*In order to enhance its solution, the algorithm goes through a certain number of iterations, which are referred to as generations. The program has terminated its execution in this instance after reaching the maximum number of generations that was specified in the code, which was one hundred iterations. On the other hand, we were able to interpret the errors that were caused by the localization. The mean localization error (PSO) is 32.85 meters on average. Using the Particle Swarm Optimization (PSO) technique, the mean error, also known as the average distance, between the actual placements of the sensor nodes and the estimated positions of those nodes is 32.85 meters. On the other hand, the mean localization error (GA) was 32.39 meters. A mean error of 32.39 meters is obtained through the use of the Genetic Algorithm (GA), while the mean localization error obtained with the hybrid algorithm is 28.56 meters: The hybrid technique, which* consists of employing PSO followed by GA, has the best performance with a mean error of 28.56 meters, which indicates that it has the lowest amount of error in comparison to the other alternatives.As a matter of fact, the mean localization error (K-Means) is 52.58 meters: With a mean inaccuracy of 52.58 meters, the K-Means clustering technique is the one that has the most potential for error. The letter'm' in the output can be interpreted as the unit of measurement for the error in the localization measurements. This indicates that the average distance between the actual positions of the sensor nodes and the estimated positions of those nodes is expressed in meters.

In Figure 5, PSO, GA, and the Hybrid Algorithm all outperform K-Means, with the Hybrid Algorithm having the lowest mean localization error. Because the optimization concluded at the maximum number of generations (100), it is possible that the algorithm did not have enough time or iterations to find a better solution. For better optimization outcomes, consider increasing the number of generations (iterations) or adjusting other parameters (such as population size).

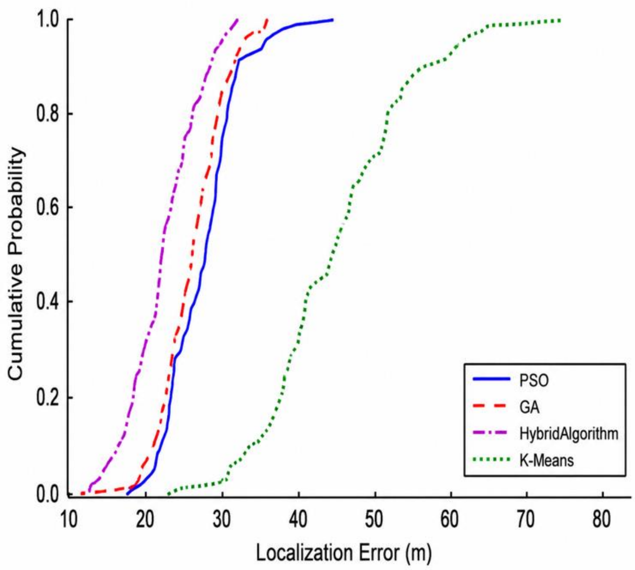


Fig. 5 Experiment with different scenario using different parameters

There are occasions when we find that GA is superior to PSO in terms of the least value of localization error, and vice versa. This is something that we discover through a number of trials and different situations that use different parameters. In Figure 6, execution time plot showing the computational complexity of each algorithm. The bar plot compares the execution times (which serve as a proxy for computational complexity) for each algorithm. The Hybrid Algorithm should be the most optimized and have the lowest execution time, as expected.

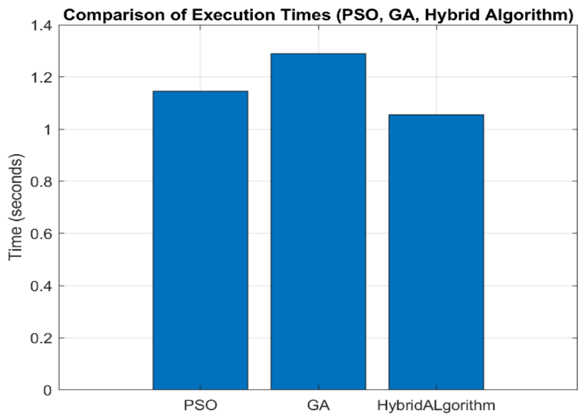


Fig. 6 Computational complexity of PSO, GA and Hybrid algorithm

All of the most recent values, however, suggest that the Hybrid Algorithm fared the best, while the K-Means algorithm had the highest error.

## I. Conclusions

The problem of localization error in wireless sensor networks (WSNs) is challenging since it involves K-Means, PSO, and GA, each of which has both advantages and disadvantages. K-Means is dependent on the configuration, yet it is efficient in terms of computing. Even if early convergence is possible, PSO is capable of searching on a global scale. In spite of its high computing cost, GA is a reliable solution for difficult problems. The precise location of sensor nodes is absolutely necessary for the efficient operation of wireless sensor networks (WSNs). Because of the features of wireless communication and the changing nature of the network environment, it is difficult to achieve reliable localization of WSN nodes. The application of optimization algorithms has emerged as a potentially useful strategy for addressing this difficulty. The purpose of this paper is to provide a full analysis of the K-mean, GA, and PSO WSN node localization algorithms, along with a new implementation hybrid approach. Several other localization strategies, such as evolutionary algorithms, swarm intelligence, metaheuristic approaches, and the classical optimization k-mean, were among the different methods that were studied. Additionally, we examined and compared various optimization techniques, taking into consideration the localization error; the hybrid approach was shown to have the lowest localization error across all situations of the proposed methodology.

## Acknowledgment

The author is very grateful to the University of Mosul/Collage of Education for Pure Science for their provided facilities, which helped to improve the quality of this work.

## Conflict of Interest

The authors declare that there is no conflict of interest

## References

[1] K. Maraiya, K. Kant, and N.Gupta, "Application based study on wireless sensor network," International Journal of Computer Applications, 21(8), 9-15, 2011, DOI:10.5120/2534-3459.

[2] L. Cheng, C. Wu, Y. Zhang, H. Wu, M. Li, C. Maple, " A survey of localization in wireless sensor network using optimization techniques," In 2018 4th International Conference on Computing Communication and Automation (ICCCA) (pp. 1-6). IEEE, DOI:10.1109/CCAA.2018.8777624

[3] A.K. Paul, T. Sato , " Localization in wireless sensor networks: A survey on algorithms, measurement techniques, applications and challenges," Journal of sensor and actuator networks, 6(4), 24, 2017 , DOI:10.3390/jsan6040024

[4] B. Peng, L. Li , " An improved localization algorithm based on genetic algorithm in wireless sensor networks," Cognitive Neurodynamics, 9, 249-256, 2015, DOI:10.1007/s11571-014-9324-y

[5] HS. Al-Olimat, RC. Green II, M Alam, V. Devabhaktuni, W. Cheng , " Particle swarm optimized power consumption of trilateration," arXiv preprint arXiv:1602.02473, 2014, DOI:10.5121/ijfcst.2014.4401

[6] A. G. Gad, "Particle swarm optimization algorithm and its applications: a systematic review," Archives of computational methods in engineering, 29(5), 2531-2561, 2022, DOI:10.1007/s11831-021-09694-4

[7] N. Primeau, R. Falcon, R. Abielmona and E. M. Petriu, "A Review of Computational Intelligence Techniques in Wireless Sensor and Actuator Networks," in IEEE Communications Surveys & Tutorials, vol. 20, no. 4, pp. 2822-2854, Fourthquarter 2018, doi: 10.1109/COMST.2018.2850220.

[8] S. Sankaranarayanan, R. Vijayakumar, S. Swaminathan, B. Almarri, P. Lorenz, and J. J. Rodrigues, " Node localization method in wireless sensor networks using combined crow search and the weighted Centroid method,"Sensors, 24(15), 4791, 2024 DOI:10.3390/s24154791

[9] J. Kumari, P. Kumar, and S. K. Singh, "Localization in three-dimensional wireless sensor networks: A survey," J. Supercomput., vol. 75, no. 8, pp. 5040–5083, Aug. 2019, doi: 10.1007/s11227-019-02781-1.

[10] N. Sharma and V. Gupta, "Meta-heuristic based optimization of WSNs localisation problem—A survey," Proc. Comput. Sci," vol. 173, pp. 36–45, Apr. 2020, doi: 10.1016/j.procs.2020.06.006.

[11] P. Saravanan, and P. Harriet, "Review on swarm intelligence optimization techniques for obstacle-avoidance localization in wireless sensor networks, " International Journal of Pure and Applied Mathematics, 119(12), 13397-13408,2018, DOI: 10.1109/ACCESS.2017.2787140

[12] E. Niewiadomska-Szynkiewicz, M. Marks, and M. Kamola, "Localization in wireless sensor networks using heuristic optimization techniques," Journal of Telecommunications and Information Technology, (4), 55-64, 2011, DOI:10.26636/jtit.2011.4.1178

[13] G. Di Fatta, F.Blasa, S. Cafiero, and G.Fortino, " Fault tolerant decentralised k-means clustering for asynchronous large-scale networks," Journal of Parallel and Distributed Computing, 73(3), 317-329, 2013 ,DOI: 10.1016/j.jpdc.2012.09.009.

[14] D. Ferreira, R. Souza, and C. Carvalho, " Qa-knn: Indoor localization based on quartile analysis and the knn classifier for wireless networks," Sensors, 20(17), 4714, 2020, DOI: 10.1016/j.tcs.2020.01.

[15] Q. Zhang, J.Wang, C. Jin, J. Ye, C. Ma, and W. Zhang , " Genetic algorithm based wireless sensor network localization ," In 2008 Fourth International Conference on Natural Computation (Vol. 1, pp. 608-613). 2008, DOI: 10.1109/ICNC.2008.206

[16] P. Sasikumar and S. Khara, “K-Means Clustering in Wireless Sensor Networks,” Fourth International Conference on Computational Intelligence and Communication Networks, Mathura, India, 2012, pp. 140-144, DOI: 10.1109/CICN.2012.136.

[17] L. Li, Y. Qiu, J. Xu , “ A K-means clustered routing algorithm with location and energy awareness for underwater wireless sensor networks,” Photonics. Vol. 9. No. 5. MDPI, 2022, DOI:10.3390/photonics9050282

[18] M. Bishop, “Pattern Recognition and Machine Learning. Information Science and Statistics,” Springer Science+Business Media, New York, 2006, DOI: 10.1117/1.2819119

[19] C. Shin, M Lee , “ Swarm-intelligence-centric routing algorithm for wireless sensor networks,” Sensors 20.18 (2020): 5164, DOI:10.3390/s20185164.

[20] R.V. Kulkarni, G.K. Venayagamoorthy, “ Particle swarm optimization in wireless-sensor networks: A brief survey,” IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 41, no. 2 (2010): 262-267.

[21] F. Tossa, W. Abdou, E.C. Ezin, P. Gouton, “ Improving coverage area in sensor deployment using genetic algorithm,” Computational Science–ICCS 2020: 20th International Conference, Amsterdam, The Netherlands, June 3–5, 2020, Proceedings, Part V 20. Springer International Publishing, 2020, DOI:10.1007/978-3-030-50426-7_30.

[22] O. Banimelhem, M. Mowafi, W. Aljoby , “ Genetic algorithm based node deployment in hybrid wireless sensor networks,” Communications and Network. 2013 Nov 14,2013., DOI: 10.4236/cn.2013.54034.

[23] M. Farooq-i-Azam, M.N. Ayyaz, “ Location and position estimation in wireless sensor networks,” Wireless sensor networks: Current status and future trends. 2016 Apr 21:179-214.

[24] K.I. Park, M. Park, “Fundamentals of probability and stochastic processes with applications to communications,” Cham: Springer International Publishing; 2018., DOI: DOI:10.1007/978-3-319-68075-0

[25] K. Kuter, “Math 345-probability,” 2023, LibreTexts.

[26] R. Janapati, C Balaswamy, K Soundararajan, “ Localization of WSN using Distributed Particle Swarm Optimization algorithm with precise references,” Journal of Communications Technology, Electronics and Computer Science, 7, 1-6, (2016),DOI: 10.22385/jctecs.v7i0.115