A novel hybrid range-free approach to locate sensor nodes in 3D WSN using GWO-FA algorithm

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Abstract
The precise node location of the sensor nodes is an essential requirement in wireless sensor networks (WSNs) to determine the place or event occurring at a particular instant of time. In WSN, existing localization schemes consider two-dimensional (2D) space, while in actual life, sensor nodes are placed in three-dimensional (3D) space. In 3D localization, there are many research challenges, such as higher computational complexity, poor location prediction, lesser coverage, and depending only on fewer anchor nodes. To address various research issues in a 3D environment we propose a range-free technique applied in an anisotropic scenario having degree of irregularity (DOI) as 0.01 using the concepts of a fuzzy logic system (FLS). Anisotropic properties of nodes are considered to determine the efficiency of Grey wolf with the Firefly algorithm. In our proposed scenario, the received signal strength (RSS) information is necessary among the target nodes and their corresponding anchor nodes for determining the location of target nodes using the information based on edge weights. These edge weights are further modeled using Hybrid Grey Wolf Optimization with Firefly Algorithm (GWO-FA) to estimate the location of target nodes. The proposed algorithm is energy efficient as a single location-aware node is used for localization. Further, the concept of virtual anchors is introduced that helps the algorithm to determine 3D positions.

Keywords Localization · WSNs · GWO-FA

Abbreviations

| Symbol | Description |
|--------|-------------|
| \((x_t, y_t)\) | Target node location for 2D scenarios |
| \((x_i, y_i)\) | Location of Anchor node in 2D scenario |
| \((d_{i,t})\) | Distance between target nodes and anchor node |
| \((x_t, y_t, z_t)\) | Location of Anchor node in 3D scenario |
| \((x_c, y_c, z_c)\) | Centroid calculation in 3D scenario |
| \(s(x_s, y_s, z_s)\) | Estimated coordinates of target node in 3D scenario |
| \(s(x_i, y_i)\) | Estimated location of a target node |
| \(s E_t\) | Error estimation |
| \(N_t\) | Number of target nodes in the WSN deployment |

1 Introduction

The advancement in MEMS and wireless technologies has led to the development of low-cost, lightweight, multifunctional, and intelligent devices known as sensor nodes (SNs). Once deployed these SNs can organize themselves to establish an ad hoc network, known as the wireless sensor network (WSN). WSNs can be used to track and detect physical phenomena in inaccessible and emergencies, where it is almost impossible to deploy the sensors nodes. These SNs can detect the physical phenomena and, using multihop propagation, the sensed data is forwarded to a centralized device known as the base station or sink node. The sensing and distribution of sensed data require the sensor, analog to digital converter (ADC), processing unit, transceiver, and battery/power supply to be equipped with these nodes. WSN implementations, however, require hundreds or thousands of SNs in the sensing field. In addition, because of their
deployment in remote locations, the power source for such SNs cannot be replaced or energized. This includes optimum usage of SNs’ computing and battery capacity so that WSN’s overall lifespan can be increased.

Most of the WSN-applications, such as forest fire monitoring, surveillance, target tracking, large-terrains monitoring, etc. require accurate knowledge of a particular location where the event has taken place. The sensed data is not useful in the absence of such knowledge. The location of sensed information can be either observed manually or deploying sensor nodes with in-built GPS [2, 3] at known locations. Manual positioning of SNs cannot be made possible as they are used in an inaccessible region while placing GPS or position finding on each node would increase the cost of using WSN and make it economically impossible to achieve [4]. Consequently, a wide variety of alternative approaches in literature [5–9] have been proposed in which random nodes (ANs) or beacon nodes are spread across the network in small quantities which are aware of their locations and location unaware nodes called target nodes determines their location with the help of anchor nodes. Localization approaches are classified broadly into two categories namely Range-based and Range-free. In a range-based localization approach, better accuracy at a cost of additional hardware integrated into SNs is achieved [10]. Few parameters such as noise and fading also degrade the performance of a technique. An alternative approach namely the range-free technique is quite economical because location determination only requires connectivity information. Due to their economic effectiveness, these localization techniques are quite common, but these techniques are less accurate as compared with range-based techniques. Improvement in the accuracy of range-free techniques is a big research challenge.

The literature reports the majority of location approaches are for two-dimensional (2D) localization [5–9], while the realistic scenario demands for SNs to be positioned in a three-dimensional (3D) environment. Although identifying locations of SNs in three-dimensional environments is nevertheless more complex and difficult.

In WSN, accurate location estimation is one of the biggest challenges. In static nodes, localization can be achieved precisely but in the case of moving nodes, this task is quite challenging. In this paper, we deployed a single anchor to locate all unknown target nodes and by using the projection of the anchor nodes virtually in six directions using hexagonal projection for targeting the unknown nodes using proposed GWO-FA. As soon as the TNs drop under the range of AN; the AN itself, and three virtual nodes are selected (as a minimum four ANs are required to determine 3D positions). The problem of Line of Sight (LoS) is minimized by deploying AN virtually in the other six directions. In this work, virtual anchors are generated using a hexagonal geometrical concept as shown in Fig. 1. At

The following benefits were offered for localization using the proposed method in this paper:

- A new technique of projecting VAs employing umbrella projection in the field for determining the exact locations of deployed sensors in a 3D environment is proposed using Hybrid GWO-FA Algorithm.
- By using the concept of VA, the line of sight (LoS) issues are minimized to a greater extent.
- Flip ambiguity issues in range-free methods are also reduced.

For locating a sensor node in 2D/3D environment, some Global Positioning System (GPS) incorporated sensor nodes (Anchor Nodes) are essential that have prior knowledge about their locations in advance by virtue of deploying manually or by equipping a (GPS). The other unlocated nodes (target nodes) obtain their locations by using existing localization algorithms. Node localization can be achieved by these two steps, i.e., distance measurement and geometric calculation. In WSNs, deployment of sensor nodes can never be envisioned as static; Dynamic WSNs are much more flexible as compared with static sensor networks as one can deploy them in any scenario and can survive with change in topology.
Connectivity, coverage and energy consumption are the critical challenges that needed to be overcome in mobility based deployment. One of the most significant and crucial challenge in dynamic WSNs is need for determining the exact locations of target node. Also for applications like space, atmospheric and underwater deployment, nodes are deployed in three dimensional space. The sensor nodes at different depths in underwater are deployed and better forecast monitoring can be done by deploying nodes at 3D space in the atmosphere.

In this paper, a new idea of projecting virtual anchor having parasol projection is used around moving target nodes to evaluate the 3D positions in an anisotropic environment using application of proposed GWO-FA and other meta-heuristics. Only single anchor node is used as a reference (anchor) node to localize the moving target node in the 3D network. In this paper, authors have considered a highly chaotic cubic structure with three layer environment and heterogeneous properties of the nodes. An anisotropic environment for 3D localization problem is considered. The location identification of deployed unknown sensor nodes in 3D environment is quite challenging as each target nodes have different battery backup status, non-uniform radiation pattern and different DOI value. The RSS values between deployed nodes and an anchor node that works based on distance measurements are modeled using FLS and further proposed GWO-FA is used to reduce errors generated in a localization process.

The remaining portion of the article is categorized as: Sect. 2 provides a detailed explanation of 3D localization techniques. In Sect. 3, FLS, GWO-FA optimization used for localization to deal with range-free WSNs is presented. The Radio irregularity model (RIM) is presented in Sect. 4, with above-mentioned algorithms. In Sect. 5, the proposed algorithm GWO-FA with Fuzzy is presented. The results and comparative analysis is presented in Sect. 6, and finally, conclusion and future work is described in Sect. 7.

2 Literature review

To solve the localization problems in WSNs, numerous localization algorithms are suggested. The connectivity information between an anchor and target node, and a number of hop counts play a crucial role in a range-free localization scheme for estimating the locations of unknown nodes. In range-free techniques, anchor node broadcast a beacon signal and the in-range target nodes sense that signal and maintain an account of the received signal strength. Further, a simple centroid method is applied to determine the coordinates of target nodes. In [7], the author proposed a range-free method based on proximity information used in a coarse-grained localization algorithm. In the proposed algorithm, the centroid method is used to calculate the 2D location of the target node by considering the location of anchor node [12]. Other well-known existing range-free algorithms are Centroid (CL) [7], Semi-Definite Position (SDP) [8], Convex [9], Approximate Point-In-Triangulation (APIT) [10], DV-Hop [11], etc. Determining the 2D coordinates of target nodes using range-free schemes is widely available in the literature. Whereas, obtaining accurate 3D coordinates of the target node is still an open research challenge. The main research contribution for 3D node localization using range-free methods in literature is as: In [13], authors proposed a hybrid localization algorithm by combining RSSI and hop distance information to calculate 3D coordinates of target node better accuracy. However, the proposed scheme is not considered for an irregular network. In [14], two range-free localization techniques based on RSS information are introduced with the application of computational intelligence methods. FLS is used to model edge weights and further optimized using an application of the genetic algorithm (GA) in the first technique. Whereas, in the second technique, the application of neural networks (NN) is used to calculate the position by considering localization as a single problem. In paper [15], the authors extended a trifling localization strategy utilizing low cost and little area WSNs. This technique is completely dispersed and satisfies a high restriction authorization for the focus on the sensor network. Authors in [16] offered a plan to improve the Monte-Carlo confinement strategy by orchestrating an adjusted hereditary calculation grounded on the amounts of the least-mean-square (LMS). Authors in [17] extended a versatile iterative localization strategy dependent on the steepest gradient descent. In 3D WSNs [18], the Authors introduced another strategy which is hybrid between the RSS and AoA localization methodology, where sensor nodes are arbitrarily scattered with unidentified transmission power and path loss exponents. In [19], the authors proposed two 3D-based range-free localization schemes using HPSO and BBO in an anisotropic environment of WSN and proposes that the non-linearity between RSS and distance can be reduced by FLS. In [20], two range-free 3D algorithms are proposed using the application of bacterial foraging optimization (BFO) and invasive weed optimization (IWO). For better localization accuracy, edge weights between the target node and their nearest anchor node are mapped using FLS, reducing computational complexity and non-linearity between RSS and distance. In [21], a range-free method is discussed for multi-hop transmission in an anisotropic networks. Hop count deviation in the shortest path and the direct path brings detoured path between nodes. Path deviation is used to estimate the new distance for the shortest path. Application of particle swarm optimization (PSO) is used for the range-free 3D DV-HOP localization method is proposed. The Proposed scheme improves the accuracy over the traditional DV-HOP method in [22]. A novel distance estimation
scheme using a centralized approach to reduce the computational and node density is proposed in [23]. To establish the 3D coordinates of the target node, minimum of four anchor nodes are required. It increases the computational complexity and anchor node density. RSS signal is affected due to the obstacles available in the environment. To overcome the computational complexity and anchor node density, a concept of virtual anchor node is proposed in this paper. Once the target node falls within the range of an anchor node, six virtual anchor nodes are projected in the proximity of this anchor node. Further, RSS and edge weight is mapped with FLS [27–30]. Application of different evolutionary algorithms is incorporated to reduce the localization error.

The method proposed here has the following attributes:

1. RSS and edge weights of an anchor node are mapped using FLS to calculate the precise locations of the unknown node.
2. The concept of a virtual anchor with their projection is done within proximity of anchor nodes.
3. A novel performance index based on proximity is proposed, to evaluate the proposed method.

3 The proposed algorithm (GWOFA)

3.1 Grey wolf optimization

Grey Wolf algorithm (GWO) is a swarm intelligence-based metaheuristic developed by Mirjalili et al. [24] based on the Grey wolves hunting mechanism. All the group members follow a hierarchy which is divided on the basis of their power and position in the group and the division is as follows. The Alpha or the leader of the pack is responsible for all the decisions making. The pack has to follow the decision of the alpha and they acknowledge and give respect to their Alpha by keeping their tails down. The Beta is the discipliner for the pack and also the advisor to the alpha. Beta is considered as the suitable substitute for the position of alpha in its absence. Beta also acts as a medium between the pack and the alpha, the decisions made by Alpha is passed on to the pack by the Beta and the feedback of the pack is again passed on to the Alpha by Beta only. The Delta wolves are the dominating wolves that are placed after Beta in the hierarchy table. These wolves dominate the Omega wolves that are the lowest in the hierarchy.

The delta wolves are further divided into five groups. The Scouts are those wolves that are responsible for the safety of the pack they act as soldiers who keep their watch on the boundaries of their territories and are always alert about their surroundings and the danger approaching. The Sentinels are those wolves whose duty is to protect the pack. These wolves are somewhere related to scout wolves. Then comes the Hunter wolves as the name justifies the hunter wolves help the upper order wolves in hunting down the prey and help in providing food to the pack. The Elder wolves are considered the most experienced ones who once used to be alpha of the pack or beta. They are all experienced in decision making, hunting techniques, and a well aware of the pack. Last but not least the caretaker wolves are the wolves that take care of the ill and the wounded, weak wolves of their pack. Now comes the last hierarchy of the pack that is the omega.

The omega wolves are the scapegoat of the pack that means these are the weakest link of the pack and are sometimes even blamed for the mishappenings in the pack. They have to follow the orders of the alpha and beta and they are even dominated by the delta wolves; the omega wolves are the lowest in the hierarchy in their position as well as power also. These wolves hunt in the following steps: Encircling, Searching, and Attacking the prey.

During the encircling, the position of the grey wolf is modified around the prey within the search space, which can be written mathematically as

\[ D = |C . X_p(t) - X(t)| \] (1)

\[ X(t + 1) = X_p(t) - A . D \] (2)

where \( t \) indicates the present iteration, \( X_p(t) \) and \( X(t) \) are the location vectors of prey and grey wolf respectively. \( A \) and \( C \) are coefficient vectors determined as

\[ A = 2a . r_1 - a \] (3)

\[ C = 2r_2 \] (4)

where \( r_1 \) and \( r_2 \) are uniformly distributed random vectors. During the hunting process, the value of \( a \) decreases linearly from 2 towards 0 and hence \( A \) also decreases using Eq. (3).

The positions of omega wolves are changed concerning the three fittest wolves of the pack as these have good knowledge regarding the location of prey. The equations used for hunting the prey are as follows:

\[ D_a = |C_1 . X_a - X|, \ D_\beta = |C_2 . X_\beta - X|, \ D_\delta = |C_3 . X_\delta - X|, \] (5)

\[ X_1 = X_a - A_1 . (D_a), \ X_2 = X_\beta - A_2 . (D_\beta), \ X_3 = X_\delta - A_3 . (D_\delta) \] (6)

\[ X(t + 1) = \frac{X_1(t) + X_2(t) + X_3(t)}{3} \] (7)

With the aim is to find the location of prey, wolves segregate themselves first and then unite together for attacking
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The prey and this condition is fulfilled by the parameter \( A \) in GWO. The parameter \( C \) helps and control the exploration rate of the searching agents and avoids stagnation by allocating a random. The basic pseudo-code for GWO is presented in Algorithm 1.

### Algorithm 1 Pseudo code of GWO algorithm [31]

1. Initialize the random search agent (grey wolf) population \( X_i \) for \( i = 1, 2, \ldots, n \)
2. Initializing various parameters: \( a, A \) and \( C \)
3. Calculate the fitness function of all search agents
4. \( X_a = \) most fit member of search space
5. \( X_b = \) next fit member of search space
6. \( X_s = \) third fit member of search space
7. While \( (t < \text{max value of iteration (T)}) \)
   - For each member in search space
     - Update their position with the equation no. (7)
   - end for
   - Update \( a, A \) and \( C \) by equations (3 and 4)
   - Evaluate the fitness value of all search agents
   - Update the value of \( X_a, X_b, X_s \)
8. \( t = t + 1 \)
9. end while
10. return \( X_a \)

### 3.2 Firefly algorithm (FA)

Firefly Algorithm (FA) is based on the concept of swarm intelligence, given by Yang [25]. FA is inspired by the light flashing behavior of fireflies and the main aim for fireflies flash is to work as a signal for other flies to get attracted to it. This population of fireflies shows some characteristic activities such as luminary flashing, attracting the partner, communication, and warning about the predator. Xin She Yang assumed a few points to formulate the algorithm:

1. Fireflies are Unisexual, which means one firefly gets attracted to other fireflies.
2. Brightness is related to attractiveness, if we consider two fireflies then the one with the least brightness will attract the one with more brightness.
3. As the distance increases, the brightness decreases.
4. If there are no fireflies left that are considered brighter then all the fireflies will move randomly in any direction.
5. Firefly’s brightness is analyzed by the fitness value of the fitness function.

This Firefly Algorithm follows some parameters such as Attractiveness, Absorption, and Randomization.

The Attractiveness parameter explains the concept of light intensity between two flies and is defined using an exponential function given by:

\[
I(r) = I_0 \exp\left(-\gamma r^2\right) \tag{8}
\]

where \( I_0 \) is the value of light intensity at \( r = 0 \); \( I \) is the light intensity at distance \( r \) from a firefly, and \( \gamma \) is the coefficient of light absorption. The absorption parameter changes the value of attractiveness from zero (0) to infinity.

As the attractiveness of fireflies is proportional to the light intensity observed by adjacent fireflies, the attractiveness can be represented as follows:

\[
\beta = \beta_0 \exp\left(-\gamma r^2\right) \tag{9}
\]

where \( \beta_0 \) is the attractiveness constant at \( r = 0 \). The Cartesian distance is the distance between fireflies \( i \) and \( j \) can be expressed as:

\[
r_{ij} = \|X_i - X_j\| \tag{10}
\]

The firefly’s \( i \) motion as drawn to another brighter firefly’s \( j \) can be depicted as follows:

\[
\Delta X_i = \beta_0 \exp\left(-\gamma r^2\right) \left(X_j^t - X_i^t\right) + \alpha (N_{rand} - 0.5) \tag{11}
\]

where \( t \) is the iteration. The term \( \alpha (N_{rand} - 0.5) \) is the randomization and the randomization parameter is analysed using Gaussian distribution. The next move of \( i \)’s Firefly can be updated as follows:

\[
X_i^{t+1} = X_i^t + \Delta X_i = X_i^t + \beta_0 \exp\left(-\gamma r^2\right) \left(X_j^t - X_i^t\right) + \alpha (N_{rand} - 0.5) \tag{12}
\]
Talking about a random walk, if the parameter $\beta_0$ is considered zero, then there is a random walk (i.e. when the fireflies move towards the best solution with the best cost in that iteration) which is corresponding to the randomization parameter.

The firefly algorithm deals with highly non-linear problems naturally. The algorithm doesn’t require a good solution to begin its iteration process. The speed of convergence in the firefly algorithm is very high which means that the probability to reach the optimal solution is high in the case of the firefly algorithm. However, the disadvantage of FA is that there are high chance of getting trapped in local optimal.

### 3.3 Proposed hybrid GWOFA

The GWO algorithm’s exploration and exploitation processes have been modified in this algorithm. Exploration and exploitation are the ones that determine the functionality of an algorithm. Any algorithm that has a good balance of both of these operations can locate the global solution quickly. As a result, the GWO must be strengthened to improve its exploitation.

The standard GWO operates on randomly generated original search agents and using parameters $A$ and $C$, grey wolves explore the area of interest and reinforce the exploration and exploitation capability of the algorithm. Also, GWO has a few parameters to change certain variables to fulfill its local and global search capabilities. Although GWO has solved a great number of engineering problems, it was found that the algorithm has some problems. The key problem facing GWO is local optima stagnation.

Concerning GWO’s exploration and exploitation capabilities, it has good exploration equations but lacks proper equations for exploitation. This has been accomplished in the current work by employing generational division. This concept of generational separation is new, and there hasn’t been much research done on it. This aids in fully exploiting and exploring the search space. We also know that in the instance of GWO, the general equations are highly effective in the exploration phase but ineffective in the exploitation phase.

Using the Firefly method, dividing iterations into two halves allows the algorithm to use new equations for the second half (when more exploitation is necessary). The basic GWO equations are used in the first half of the solution space. FA is extremely efficient in exploitation operations, hence equation change based on the FA will undoubtedly produce efficient outcomes.

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**Algorithm 2 Pseudo code of proposed GWOFA**

1. Initialize the random search agent (grey wolf) population $X_i(i=1,2,\ldots,n)$
2. Initializing various parameters: $a$, $A$, $C$, $\beta_0$ and $\alpha$
3. Initialize the max value of iteration: $T$
4. Calculate the fitness function of all search agents
5. $X_\alpha =$ most fit member of search space
6. $X_\beta =$ next fit member of search space
7. $X_\delta =$ third fit member of search space
8. While ($t < T/2$)
   1. For each member in search space
   2. Update their position with the equation no. (2)
   3. end for
   4. update $a$, $A$ and $C$ by equations (3 and 4)
   5. Evaluate the fitness value of all search agents
   6. Update the value of $X_\alpha$, $X_\beta$, $X_\delta$
   7. else
   8. For each member in search space
   9. Update their position with the equation no. (13)
   10. end for
   11. update $a$, $A$ and $C$ by equations (3 and 4)
   12. Evaluate the fitness value of all search agents
   13. Update the value of $X_\alpha$, $X_\beta$, $X_\delta$
   14. $t = t + 1$
15. end while
16. return $X_\alpha$
Algorithm 2 shows a pseudo code of GWOFA algorithm. An exploitation activity inspired by the FA principles is introduced to enhance the exploitation aspect to solve the problems arising from the weak exploitation process. In the suggested algorithm process, the FA definition affects the GWO algorithm and is called the GWOFA. This change will help to resolve the current weaknesses of the basic GWO characteristics of slow and premature convergence.

As discussed, the number of iterations in the proposed GWOFA algorithm is divided into two half. In the first half, the regular GWO’s general Eq. (7) is used, and then in the second half, a new search equation is used. The current equation is replaced with FA position update equation as follows.

\[ X_{new}(t+1) = \frac{X_{1new}(t) + X_{2new}(t) + X_{3new}(t)}{3} \]  

(13)

where \( X_{1new}(t) \), \( X_{2new}(t) \), and \( X_{3new}(t) \) are the position vectors of alpha, beta and delta grey wolves inspired from FA for second half of iterations.

\[ X_{1new} = X_1 + \beta_0 e^{-\gamma \cdot r_1^3} (X_j - X_1) + \alpha (N_{rand} - 0.5) \]  

(14)

\[ X_{2new} = X_2 + \beta_0 e^{-\gamma \cdot r_2^3} (X_j - X_2) + \alpha (N_{rand} - 0.5) \]  

(15)

\[ X_{3new} = X_3 + \beta_0 e^{-\gamma \cdot r_3^3} (X_j - X_3) + \alpha (N_{rand} - 0.5) \]  

(16)

### 3.4 Fuzzy logic system (FLS)

It is a type of many-valued rationale, in which real estimations of variables might be any number in the vicinity of 0 and 1. The term fuzzy logic was given in the proposal of fuzzy set theory submitted by Lotfi Zadeh in 1965. This deals with an idea of halfway truth, where real value may lie between totally true and false. From control theory to artificial intelligence, fuzzy logic has been applied and is being applied by a lot of researchers.

It enhances the robustness of the system. The fuzzy logic configuration of consists of input scaling factor, fuzzifier, inference engine, defuzzifier, and the output scaling factor, as shown in Fig. 2.

- **Input/Output Scaling Factor:**—Basically, it is defined as a nonlinear mapping of the input data set to the scaler output data. The input scaling factor in FLS is used for transformation between crisp input data and universe of discourses of the fuzzy input variables and output scaling factor is used to tune the output gain of the FLS.

- **Fuzzifier:**—The gathered crisp input data set is fuzzified at this block. This conversion is done by using a set of fuzzy linguistic variables, linguistic terms, and membership functions.

- **Inference Engine:**— The primary work of the inference engine is decision making. The output of the inference engine is always fuzzy irrespective of its input, i.e., whatever is the input (fuzzy or crisp) of the inference engine, the output is always fuzzy. Rule base, database, decision-making unit, fuzzification interface unit are the functional blocks of fuzzy inference system.

- **Defuzzifier:**—The defuzzification of the fuzzy data set is done at this block. This defuzzification is done by using membership functions and crisp output is taken from this block.

The fuzzy flow model and pseudo code is given in (17) and Algorithm3, where x represents an input variable that contains the RSS values from an anchor node and y signifies an output value, i.e. the edge weight for every target node is given by

\[ R_i : if \ x \ is \ A_i \ then \ y \ is \ W_i \]  

(17)
4 Statistical testing of GWOFA algorithm

Table 1 provides a set of ten CEC 2019 benchmark test functions known as the "100-Digit Challenge" [26] for GWOFA testing. All of these test functions can be scaled up or down. GWOFA’s efficiency is assessed by comparing it to FPA, GWO, SSA, CS, DA, FDO, and SCA. With the support of 30 agents, each algorithm goes through 500 iterations. For each of the methods under consideration, the results are given in terms of the best, worst, mean, and standard deviation values for 30 independent runs. GWOFA outperforms other algorithms except in CEC03, CEC(06–07), and CEC(9–10) (see Table 2). Figure 3 shows the convergence graph and box plot of various approaches for various benchmark functions.

GWOFA’s results for function CEC01 are better than other algorithms in terms of the best, worst, average, and median values achieved. GWO, CS, and GWOFA are all capable of identifying an optimal solution for function CEC02, but FDO is demonstrated to be the best. For the CEC03 function, most algorithms can give a nearly globally optimal solution, although FDO is superior to other methods in terms of least standard deviation. GWOFA counteracts others in terms of fitness performance when it comes to CEC04 and CEC05. GWOFA’s results for function CEC07 are the worst when compared to other methods. GWOFA’s scores for function CEC08 are better in terms of best-acquired fitness performance. GWOFA’s results for the functions CEC09 and CEC10 are comparable to those of other approaches.

Figure 2 shows box plots of competing algorithms. These plots are used to evaluate the efficiency of an algorithm in this scenario. In most cases, the suggested GWOFA is more cost-effective in terms of fitness values because the median value of GWOFA is lower. As a result, the overall performance of GWOFA is better than other optimization strategies.

5 Radio irregularity model

Many existing localization strategies use an ideal spectrum without considering DOI’s. But it’s not possible to achieve in practice. So radio-irregularity is one of the major aspects for studying a certain pattern in real situations. Radio irregularity is one of the primary concerns that cannot be neglected in wireless networks [29]. The effect of certain radio irregularities is also examined in our algorithm. As the variations in
Table 2 CEC 2019 test suite for competitive algorithms

| Function | Parameters | Best     | Worst    | Average  | Median   | Std. dev |
|----------|------------|----------|----------|----------|----------|----------|
| CEC01    | FPA        | 1.37E+08 | 1.20E+09 | 5.03E+08 | 4.41E+08 | 2.78E+08 |
|          | GWO        | 5.15E+04 |          |          |          |          |
|          | SSA        | 4.18E+08 | 2.63E+10 | 5.38E+09 | 2.68E+09 | 6.16E+09 |
|          | CS         | 1.00E+10 | 1.00E+10 | 1.00E+10 | 1.00E+10 | 0.00E+00 |
|          | DA         | 2.03E+09 | 1.67E+11 | 4.95E+10 | 4.09E+10 | 4.74E+10 |
|          | FDO        | 7.32E+07 | 7.66E+09 | 1.34E+09 | 6.37E+08 | 1.72E+09 |
|          | SCA        | 8.91E+05 | 3.58E+10 | 6.65E+09 | 3.07E+09 | 9.21E+09 |
|          | GWOFA      | 3.86E+04 |          |          |          |          |
| CEC02    | FPA        | 1.81E+09 | 3.37E+01 | 2.24E+01 | 2.16E+01 | 3.66E+00 |
|          | GWO        | 1.73E+01 | 1.73E+01 | 1.73E+01 | 1.73E+01 | 2.69E-04 |
|          | SSA        | 1.73E+01 | 1.74E+01 | 1.73E+01 | 1.73E+01 | 1.48E-02 |
|          | CS         | 1.73E+01 | 1.73E+01 | 1.73E+01 | 1.73E+01 | 6.24E-05 |
|          | DA         | 1.74E+01 | 3.16E+02 | 6.00E+01 | 3.77E+01 | 6.71E+01 |
|          | FDO        | 1.73E+01 | 1.73E+01 | 1.73E+01 | 1.73E+01 | 1.65E-05 |
|          | SCA        | 1.74E+01 | 1.77E+01 | 1.75E+01 | 1.75E+01 | 7.24E-02 |
|          | GWOFA      | 1.73E+01 | 1.73E+01 | 1.73E+01 | 1.73E+01 | 3.44E-04 |
| CEC03    | FPA        | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.47E-07 |
|          | GWO        | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 2.18E-07 |
|          | SSA        | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.93E-13 |
|          | CS         | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 9.07E-11 |
|          | DA         | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 5.25E-04 |
|          | FDO        | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.40E-11 |
|          | SCA        | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 4.73E-05 |
|          | GWOFA      | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.27E+01 | 1.53E-08 |
| CEC04    | FPA        | 9.52E+00 | 1.92E+02 | 1.37E+02 | 1.37E+02 | 2.50E+01 |
|          | GWO        | 2.59E+01 | 9.39E+01 | 5.88E+01 | 5.57E+01 | 1.82E+01 |
|          | SSA        | 1.59E+01 | 7.16E+01 | 4.04E+01 | 3.88E+01 | 1.55E+01 |
|          | CS         | 1.79E+01 | 3.91E+01 | 2.74E+01 | 2.56E+01 | 6.04E+00 |
|          | DA         | 2.17E+01 | 9.05E+02 | 3.80E+02 | 3.94E+02 | 2.72E+02 |
|          | FDO        | 1.10E+01 | 8.56E+01 | 3.76E+01 | 3.28E+01 | 2.05E+01 |
|          | SCA        | 4.53E+02 | 2.06E+03 | 1.15E+03 | 1.10E+03 | 4.12E+02 |
|          | GWOFA      | 8.50E+00 | 6.65E+01 | 4.29E+01 | 4.68E+01 | 1.60E+01 |
| CEC05    | FPA        | 1.38E+00 | 1.73E+00 | 1.58E+00 | 1.60E+00 | 8.71E-02 |
|          | GWO        | 1.11E+00 | 1.88E+00 | 1.42E+00 | 1.32E+00 | 2.55E-01 |
|          | SSA        | 1.04E+00 | 1.50E+00 | 1.25E+00 | 1.24E+00 | 1.39E-01 |
|          | CS         | 1.03E+00 | 1.12E+00 | 1.06E+00 | 1.06E+00 | 1.69E-02 |
|          | DA         | 1.13E+00 | 2.18E+00 | 1.49E+00 | 1.42E+00 | 3.15E-01 |
|          | FDO        | 1.06E+00 | 1.54E+00 | 1.19E+00 | 1.15E+00 | 1.23E-01 |
|          | SCA        | 1.93E+00 | 2.32E+00 | 2.17E+00 | 2.17E+00 | 8.31E-02 |
|          | GWOFA      | 1.01E+00 | 1.74E+00 | 1.16E+00 | 1.07E+00 | 2.00E-01 |
| CEC06    | FPA        | 9.50E+00 | 1.15E+01 | 1.06E+01 | 1.07E+01 | 6.07E-01 |
|          | GWO        | 9.91E+00 | 1.19E+01 | 1.08E+01 | 1.08E+01 | 5.93E-01 |
|          | SSA        | 1.41E+00 | 1.02E+01 | 5.01E+00 | 5.04E+00 | 2.06E+00 |
|          | CS         | 7.35E+00 | 1.01E+01 | 9.08E+00 | 9.36E+00 | 7.90E-01 |
|          | DA         | 5.09E+00 | 1.11E+01 | 8.78E+00 | 8.78E+00 | 1.51E+00 |
|          | FDO        | 9.30E+00 | 1.23E+01 | 1.10E+01 | 1.11E+01 | 7.63E-01 |
|          | SCA        | 9.52E+00 | 1.17E+01 | 1.07E+01 | 1.07E+01 | 5.72E-01 |
transmitting the signal with different RF powers and different path loss will lead to an irregularity in the radio pattern. To establish the anisotropic properties of the propagation media the Radio Irregularity Model (RIM) is considered [30]. A DOI parameter (degree of irregularity) [31] in Fig. 4 calculates the irregularity in the radiation pattern.

### 5.1 Problem formulation

A three-layer structure is considered for locating sensor nodes in a 3D scenario using anchor and target nodes positioned in a three-layer structure. The anchor node is mobile and it moves randomly at regular intervals of time. The whole region is grouped into grids and under the range of an anchor node. The movement of an anchor node is assumed to cover the entire region. An anchor node transmits beacon information and all unknown nodes receive it and transform it into distance information. A range-free localization scheme is applied in this paper and the gathered RSSI information is sufficient enough to calculate distance.

As soon as the target node falls within the range of the anchor node, a novel concept of selection of virtually deployed anchors is introduced (for each target node) to estimate their location. In every movement, an anchor node estimates a Euclidean distance. If Euclidean distance is less than the anchor node’s range then each target node is considered as localizable and possibly within a radius circle. Along with anchor node and six virtually assumed anchors
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Fig. 3 Boxplot and convergence graphs for CEC 2019 benchmark functions
Fig. 3 continued
are transmitted using same transmitting range (as minimum 3/4 nodes are necessary to locate target nodes in 2D/3D environment. In the range-free method only RSS information is sufficient enough to measure the distance between a target node and an anchor node. While gathering RSS information a signal may change its path due to blockage in environmental conditions. The most used propagation medium in WSN is path loss, lognormal, and Rayleigh fading. As RSS signal varies over shorter distances. All environmental parameters that degrade the performance are considered in our work. The received signal power is modeled using (18)

\[ P_{revj} = \gamma^2 \left( \frac{P_{tx}}{\sum_{i}^{n} d_{ij}} \right) 10^{\frac{X_j}{10}} \]

where \( \gamma \) represents Rayleigh distribution and accounts for multipath fading, \( P_{tx} \) is transmitted power, \( c \) is determined by antenna characteristics, \( \alpha \) represents path loss component, \( 10^{\frac{X_s}{10}} \) accounts for shadowing effect, \( X_s \sim N(0, \sigma_d^2) \), \( k_i \) is path loss component due to anisotropic environment, and \( N \) represents a Gaussian random variable with zero mean and variance \( \sigma_d^2 \). The measurement on the basis of RSS distance between the target and an anchor node is given by (19)

\[ d_{ij} = d_{ij} \sqrt{\sum_{i}^{n} \frac{1}{d_{ij}}} \]

5.2 GWO-FA and fuzzy logic based localization concept

In this work, a single anchor node is considered to locate all target nodes deployed in a 3D sensing field. The target nodes are dispersed in two different layers (i.e., bottom and middle layer) and an anchor is positioned at the top layer. The main task of using an anchor node is to transmit a beacon signal which helps the target nodes to estimate their location. Whenever a target node drops within the range of an anchor node, it listens to a beacon for a fixed time frame and collects RSS information of an anchor node. The Euclidean distance between an anchor and target node is calculated and the concept of virtual anchors is introduced in six distinct directions with an angle difference of 60° each at an equal distance for anchor node. Due to heterogeneity property radio propagation is spherical due to irregularity in radiation pattern and the transmission range is not equivalent in all directions. The anchor node’s location is known either by GPS or any other means.

The below steps are followed for 3D location determination of a target node.

1. The unknown sensor nodes are placed in between and beneath layers of a 3D cubic structure randomly and a known sensor is placed on the top. The procedure of virtual anchors having parasol projection is considered in Fig. 5.

2. Using \( d_i^\wedge = d_i - (D_p + F) \), the distance among anchor and a corresponding target node is calculated. Where, \( d_i \) is the actual distance, \( D_p \) is DOI adjusted path loss and \( F \) represents fading effect.

3. The RSS measurement is done using (20)

\[ RSS_{ij} = \frac{v}{d_{ij}^{\alpha}} \]

4. Check whether or not the anchor node and virtual anchors are \( \geq 4 \)

5. The edge weights are calculated and modeled using FLS.

6. To achieve accurate target node locations these edge weights and fuzzy sets are generated using various meta-heuristic algorithms.

7. The target node locations using the prior knowledge of edge weights is calculated using

\[ (x_t, y_t, z_t) = \frac{(w_1x_1 + \ldots + w_kx_k)}{\sum_{i=1}^{k} w_i}, \]

\[ (w_1y_1 + \ldots + w_ky_k)}{\sum_{i=1}^{k} w_i}, \]

\[ (w_1z_1 + \ldots + w_kz_k)}{\sum_{i=1}^{k} w_i} \]

(21)
5.3 Fuzzy Modeling for Edge weights with different meta-heuristics:

To overcome the nonlinearity between distance and RSS measurements, the FLS with Mamdani implication is used to counteract the nonlinearity and develop a relation among RSS and edge weight of an anchor node. Algorithm 4 describing the flow of fuzzy modelling is given as:

Algorithm 4: Localization using Parasol Projection
1. Form of fuzzy model is given by (17)
2. Value of input is $[0, RSS_{max}]$, where $RSS_{max} = 100 \text{ db}$ represents the maximum value
3. This value is grouped into five membership functions
4. Value of output variable is taken as $[0, w_{max}]$, where $w_{max} = 1$ represents the maximum edge weight
5. Membership functions of output variable generated by GWO-FA
6. Complete rule set have been made
7. To each rule set a degree of importance is applied
8. By using Mamdani implication operator, from these fuzzified values a single crisp set is taken
9. For FLS tuning, the output variable membership functions are optimized

The fuzzy flow model is given in (22), where $x$ represents an input variable that contains the RSS values from an anchor node and $y$ signifies an output value, i.e. for every target node the edge weight of an anchor node

\[ R_i : \text{if } x \text{ is } A_i \text{ then } y \text{ is } W_i \]  

(22)

The input containing RSS values is grouped among five different membership functions using triangular, S type, and Z type function represented in Fig. 4. To complete the rule set the membership functions are categorized as $W_i$ is either very low, low, medium, high, and either very high as given in Table 3. The degree of importance for every each rule to be applied is given by

\[ \text{Degree of Importance} = \mu(x) \times \mu(y) \]  

(23)

By focusing on eqn (18) the redundant rules given in Table 4 are replaced by new final rules given by Table 5 (Fig. 6).

6 Simulation results and performance analysis

The proposed GWO-FA algorithm with fuzzy is implemented in MATLAB environment with a single anchor node. A cubical area of $10l \times 10l \times 10l$ is assumed where an anchor node is kept fixed and target nodes are mobile. An anchor node is positioned at the top layer having a transmission range of $R = 10l$. With the movement of the target node, an anchor node communicates with target node only if it is within the range. As soon as target nodes drop within the anchor node’s range, six virtual anchors are projected using parasol projection and out of these six three virtual anchor nodes are selected to determine 3D location. The edge weights between every target node and an anchor, virtual anchors are used and modelled using Fuzzy Logic System (FLS). After modeling them using FLS the optimization of these edge weights is done using various meta-heuristics. The RSS parameter is considered as the simulation parameter and is given as

| Table 3 | Rule base |
|---------|-----------|
| S. No   | Antecedent | Consequent |
| 1       | When value of RSS is Very Low | Then Very Low EW |
| 2       | When value of RSS is Very Low | Then Low EW |
| 3       | When value of RSS is Very Low | Then Medium EW |
| 4       | When value of RSS is Very Low | Then High EW |
| 5       | When value of RSS is Very Low | Then Very High EW |
| 6       | When value of RSS is Low | Then Very Low EW |
| 7       | When value of RSS is Low | Then Low EW |
| 8       | When value of RSS is Low | Then Medium EW |
| 9       | When value of RSS is Low | Then High EW |
| 10      | When value of RSS is Low | Then Very High EW |
| 11      | When value of RSS is Medium | Then Very Low EW |
| 12      | When value of RSS is Medium | Then Low EW |
| 13      | When value of RSS is Medium | Then Medium EW |
| 14      | When value of RSS is Medium | Then High EW |
| 15      | When value of RSS is Medium | Then Very High EW |
| 16      | When value of RSS is High | Then Very Low EW |
| 17      | When value of RSS is High | Then Low EW |
| 18      | When value of RSS is High | Then Medium EW |
| 19      | When value of RSS is High | Then High EW |
| 20      | When value of RSS is High | Then Very High EW |
| 21      | When value of RSS is Very High | Then Very Low EW |
| 22      | When value of RSS is Very High | Then Low EW |
| 23      | When value of RSS is Very High | Then Medium EW |
| 24      | When value of RSS is Very High | Then High EW |
| 25      | When value of RSS is Very High | Then Very High EW |
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Table 4 Edge weights (with redundancy removed)

| S.No | Antecedent            | Consequent            |
|------|-----------------------|-----------------------|
| 1    | When value of RSS is Very Low | Then Very Low EW      |
| 2    | When value of RSS is Low   | Then Low EW            |
| 3    | When value of RSS is Medium | Then Medium EW        |
| 4    | When value of RSS is High  | Then High EW           |
| 5    | When value of RSS is Very High | Then Very High EW     |

Table 5 Parameter settings

| Algorithm | Parameters          |
|-----------|---------------------|
| PSO       | NP = 100; D = 3; Gmax = 200; c1, c2, = 2; w = 0.729, DOI = 0.01 |
| HPSO      | NP = 100; D = 3; Gmax = 200; c1, c2, c3 = 1.494; n = 0.1; w = 0.729, DOI = 0.01 |
| BBO       | NP = 100; D = 3; Gmax = 200; pm = 0.05, DOI = 0.01 |
| FA        | NP = 100; D = 3; Gmax = 200; a = 0.2; γ = 0.96, DOI = 0.01 |
| GWO       | NP = 100; D = 3; Gmax = 200; a = [2 to 0]; C = [0 to 2], DOI = 0.01 |
| GWO-FA    | NP = 100; D = 3; Gmax = 200; a = [2 to 0]; C = [0 to 2], α = 0.2; γ = 0.96, DOI = 0.01 |

NP population size, Gmax number of iterations, c1 cognitive learning parameter, c2 social learning parameter, c3 neighborhood learning parameter

RSS = Sending Power − (DOI adjusted path loss + Noise)  
(24)

DOI Adjusted Path loss = PathLoss × Ki; Where Ki is used to represent variations in path loss in different directions.

In the initial step, we have assumed anchor at the centre position of the top layer and afterward it moves randomly at regular intervals of time. We have assumed nine movements an anchor node in this paper and seen a better performance in terms of location identification of target nodes with better accuracy.

The WSN localization simulations are conducted to show the effectiveness of the proposed intelligent localization methods in MATLAB environment with 80 target nodes deployed randomly in a sensor field of 10 l × 10 l × 10 l (here unit is in meter). Each anchor has a maximum transmission range of R = 10 l units. A target node can communicate with an anchor node if its distance from an anchor node is less than the target node’s transmission range.

The linear combination of RSS and proximity is proposed in this work, whereas other indices are the standard indices available in the literature, i.e., location error and average location error.

1. Linear Combination:

\[ LC = \frac{a \times \text{promixity} + b \times \text{RSS}}{a + b} \]  
(25)

where

\[ \text{promixity} = \frac{1}{\text{distance between anchor node and target node}} \]

where a and b values lies between 0 and 1.

2. Location Error:

\[ LE = \sqrt{(x_{\text{est}} - x_{\text{act}})^2 + (y_{\text{est}} - y_{\text{act}})^2 + (z_{\text{est}} - z_{\text{act}})^2} \]  
(26)

3. Average Location Error:

\[ ALE = \frac{\sqrt{(x_{\text{est}} - x_{\text{act}})^2 + (y_{\text{est}} - y_{\text{act}})^2 + (z_{\text{est}} - z_{\text{act}})^2}}{\text{number of target nodes}} \]  
(27)

where \((x_{\text{est}}, x_{\text{act}}, y_{\text{est}}, y_{\text{act}}, z_{\text{est}}, z_{\text{act}})\) are actual and the computed coordinates of a target node.

In this paper, various localization methods have been implemented for comparison: the simple centroid method [32], the weighted centroid method [33], and other meta-heuristics Figs. 7, 8, 9, and 10 show the results of proposed GWO-FA Algorithm. Further, it is observed that target nodes localized by GWO-FA is just near to actual positions of the target nodes as compare to other metaheuristics. The location error (between actual position and calculated position) for each target node is further tabulated in Table 6. It is observed that the methods proposed in this paper perform better as compared to earlier proposed methods. Further, it is observed that proposed GWO-FA based algorithm gives better accuracy and fast convergence.

Thirty trials with each meta-heuristics are applied to optimize RSS value and the edge weights, Figs. 7, 8, 9, 10, and Table 6 show that the results obtained with the proposed GWO-FA algorithm provide better performance as compared with other meta-heuristics.

The below-mentioned parameters are assumed for comparison of proposed scheme with other meta-heuristics.

In this paper, the proposed algorithm GWO-FA is compared with other meta-heuristics available in the literature. The simulation results of the proposed scheme provide better results using a single anchor node with less localization error.
In Table 6, it is stated that our mobility-based algorithms are compared with static procedures that are available in the literature. This table gives the idea that the mobility-based algorithm proposed in our manuscript outperforms the static algorithms despite having several challenges due to mobile scenarios (Fig. 11).

7 Conclusions and future scope

A method for range-free 3D node localization has been presented using a variety of meta-heuristics methods. The top layer is considered to have a single mobile anchor node, and the target nodes and anchor node are deployed across three-layer boundaries in an anisotropic environment. The anchor node traverses the top layer, whereas the target nodes are spread throughout the lower levels. To model the change in environmental conditions, a superimposed fading model is utilized. To establish the 3D coordinates of each target node, a unique notion of virtual anchor nodes is proposed. The non-linear relationship between Received Signal Strength (RSS) and distance has been minimized by assigning edge weights to each target node and anchor node to identify the target node’s position. To reduce computational complexity, we modeled RSS and edge weights using a Fuzzy Logic System (FLS). The proposed methods do not require much hardware.
to get the distance information between the target node and its neighboring anchor nodes, only RSS information between them is sufficient for the target nodes to estimate their positions. Additionally, the RSS and edge weights membership function bases are optimized using various metaheuristics and a novel proposed GWO-FA to decrease position error. The proposed algorithm's simulation results were compared to those of previously published static methods such as centroid, weighted centroid, BBO, HPSO, BFO, TLBO, IWO, MIWO, and it was determined that the proposed method GWO-FA achieves a higher level of localization accuracy than the others. Range-free localization algorithms are cost-efficient but have lower levels of accuracy, a range-free localization algorithm needs to be developed in such a manner that it does not require costly RSS-based techniques but can determine the node locations with high accuracy. In future, a combination of both range-based and range-free localization algorithms is found to be the best solution for various problems on localization.
Fig. 9 GWO-FA (proposed) based node localization

Fig. 10 RF GWO-FA (proposed) based node localization
Table 6 Comparison of various meta-heuristics in context of static and dynamic scenario

| Static/mobile | Technique           | Max error | Min error | Average error |
|---------------|---------------------|-----------|-----------|---------------|
| Static        | Centroid            | 3.892     | 0.129     | 2.910         |
| Static        | Weighted centroid   | 2.751     | 0.0610    | 1.432         |
| Static        | HPSO + Fuzzy        | 0.991     | 0.088     | 0.812         |
| Static        | BBO + Fuzzy         | 0.868     | 0.079     | 0.658         |
| Static        | BFO + Fuzzy         | 0.831     | 0.067     | 0.551         |
| Static        | IWO + Fuzzy         | 0.796     | 0.043     | 0.486         |
| Static        | TLBO + Fuzzy        | 0.768     | 0.032     | 0.481         |
| Static        | MIWO + Fuzzy        | 0.594     | 0.025     | 0.475         |
| Static        | GWO-FA + Fuzzy      | 0.531     | 0.015     | 0.452         |
| Mobile        | HPSO + Fuzzy        | 0.681     | 0.078     | 0.449         |
| Mobile        | BBO + Fuzzy         | 0.768     | 0.059     | 0.512         |
| Mobile        | BFO + Fuzzy         | 0.712     | 0.057     | 0.431         |
| Mobile        | IWO + Fuzzy         | 0.796     | 0.043     | 0.486         |
| Mobile        | TLBO + Fuzzy        | 0.723     | 0.002     | 0.429         |
| Mobile        | MIWO + Fuzzy        | 0.594     | 0.005     | 0.288         |
| Mobile        | GWO-FA + Fuzzy      | 0.531     | 0.015     | 0.227         |

Fig. 11 RF GWO-FA based node distance estimation between actual and estimated nodes

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