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Dimension based Localization Technique in Internet of Things: A Fuzzy Driven Approach for Mobile Target

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The process of extracting the accurate geographical position of mobile target has a dominant efficacy on the performance of a wireless sensor network. The location information of moving node is a mandate requirement to process the data collected by the sensor nodes. The localization technique that finds the exact location of target node in a Internet of Things framework is applied for domain-specific applications. In this paper, a fuzzy driven approach embedded with Dimensionality based Particle Swarm Optimization algorithm is proposed. The Dimensionality based Particle Swarm Optimization (DPSO) is a variant of the traditional PSO and the particle deployment is done in each dimension of the co-ordinate of target node to obtain optimized values in the individual dimension. The anisotropic properties of propagation media (*i.e.*, environmental factors) and the characteristics of devices (*i.e.*, sending power) are considered to compute the Received Signal Strength (RSS). An Adaptive Neuro-Fuzzy Inference System (ANFIS) is developed to study these radio irregularities and a distinct set of rules are framed in the training phase to select the appropriate attenuation exponent value. The proposed algorithm can be applied in outdoor anisotropic environments. The DPSO model outperforms well in all localization instances for three test cases containing different trajectories, where the path of target node is randomly chosen. The results were compared with the existing algorithms such as PSO and HPSO in terms of average localization error and number of iterations required to attain convergence.

Keywords: adaptive neuro fuzzy inference system, dimensionality based particle swarm optimization (DPSO), Internet of Things (IoT), Received Signal Strength (RSS), target node, localization

1. INTRODUCTION

Internet is adopted as hassle-free technology for establishing person to machine and machine to machine communication. There are rapid advancements in internet technologies that are noticed through smart wearable devices, Bluetooth, Global Positioning System (GPS), and Radio Frequency Identification (RFID) tags. These technologies play a significant role in the daily activities of humans and the broad spectrum of smart human interacted design leads to Internet of Things. Wireless Sensor Networks (WSN) is a subpart of IOT, which has applications in the fields such as defense, health-care, astronomy, agriculture, *etc.* The WSNs has emerged as an interesting field of research that draws the attention of researchers to provide solutions for location identification problem, data acquisition problem, and security threats [1]. So, the research was carried out in discovering a suitable solution, which satisfies the stringent constraints shown by nodes

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such as limited energy, restricted GPS functionality, and limited communication bandwidth during the installation phase. However, the primary focus was given for identifying the accurate location of the unknown target node. This process is known as localization.

The technocrats concentrate on developing budgetary systems with a minimum number of location-configured (*i.e.*, GPS-enabled) nodes while the remaining mobile target nodes depend on these location-configured nodes for identifying its location. The location-configured nodes are dynamic in nature and it is capable of recognizing its position on their own in the absence of external devices. The nodes with inbuilt GPS units are termed as anchor nodes, while the remaining nodes in the network are termed as target nodes. The position of target nodes are estimated using the location information of anchor nodes, provided that those nodes must lie within the transmission range of anchor nodes. The nature of the system may vary depending on its geographical setup, inventory regulations, network standards, and application scenarios. Hence, whatever may be the environment setup, the network administrator expects a reliable model to estimate the accurate position of target nodes.

In the recent days, several works concentrated to incorporate the influencing characteristics of network in the localization process. There exists a gap in finding a feasible method to model the behaviour of network. Hence, a fuzzy inference system (FIS) is used for efficiently modelling the network into a reliable system. The neuro-fuzzy modelling is a rule-based character analyzer that allows for a model interpretation in a way similar to human understanding [2]. The adaptive neuro-fuzzy inference system (ANFIS) is an advanced technique of fuzzy based systems for modelling and simulation of complex systems [3, 4]. In the proposed localization technique, the ANFIS technique builds the complex systems to imitate the characteristics of anisotropic networks and resource-constrained network configurations. This technique is widely suitable to different IoT architectures such as cloud based architecture and fog based architecture [5]. So, the ANFIS model is used to learn the external factors present in prior to localization process because the network characteristics changes depending on the geographical location. The efficiency of the ANFIS engine depends on the accurateness of the generated rule-base.

The trilateration technique was proposed in [6], which requires the distance estimates of at least three neighbourhood anchor nodes to compute the location of an unknown target node. But, the node deployment regions are multidimensional in all practical applications and this positioning method is unsuitable. The nodes are deployed with constraints over three layer boundaries (*i.e.*, anisotropic network). This topology also uses Received Signal Strength (RSS), which estimates the strength of the signal between two nodes. Therefore, the performance of the existing algorithms is not appreciable in terms of success rate and accuracy level due to higher dimensionality space. Subsequently, to overcome these pitfalls, the optimization algorithms are employed to develop an accurate positioning method. Particle swarm optimization (PSO) is a stochastic optimization technique, where the population consisting of particles is called as swarm. These particles move in the search space by obeying rules that are influenced by bird flocking behaviour [7]. The particles fail to fall under the global optimum solution because of random deployment and it leads to immature convergence. In [8], the authors have proposed the environment variables for particle swarm optimization framework, but the behaviour of dynamic nodes is not considered. This reduces the definiteness of the objective function. In the proposed technique, a stipulated set of parameters are fixed and dimension pruning is used for defining an appropriate objective function. Further, this non-increasing objective function is utilized for location identification.

In [9], we proposed the application of DPSO for range-based, distributed 3D localization with static nodes in anisotropic environment. In this paper, the application of DPSO is used to perform localization of mobile nodes with a neuro-fuzzy model to mimic the environment behaviour. The pre-processing steps are carried out by the model to interpret the external factors of node deployment region. The true distance estimates are computed from the distinct RSS values using a Fuzzy Inference System (FIS) rule base, which is generated from the model. The DPSO follows a dimension based optimization technique that takes the essence of PSO by considering each dimension to estimate the location of the target node, which moves in a random path. Hence, a neuro-fuzzy model is embedded with the DPSO-localization process for attaining accurate position of the mobile target node. The outcomes of this paper are as follows,

1. Adaptive neuro-fuzzy model is employed to train the system by giving RSS values as input and its corresponding attenuation exponent (α) is computed as output.
2. FIS rule base consisting of valid IF-Then rules are generated in prior to the localization.
3. DPSO, follows a dimensionality based estimation method for computing the location of moving target node in different instances. The target nodes are simulated to move on three different paths, which are chosen in random manner.

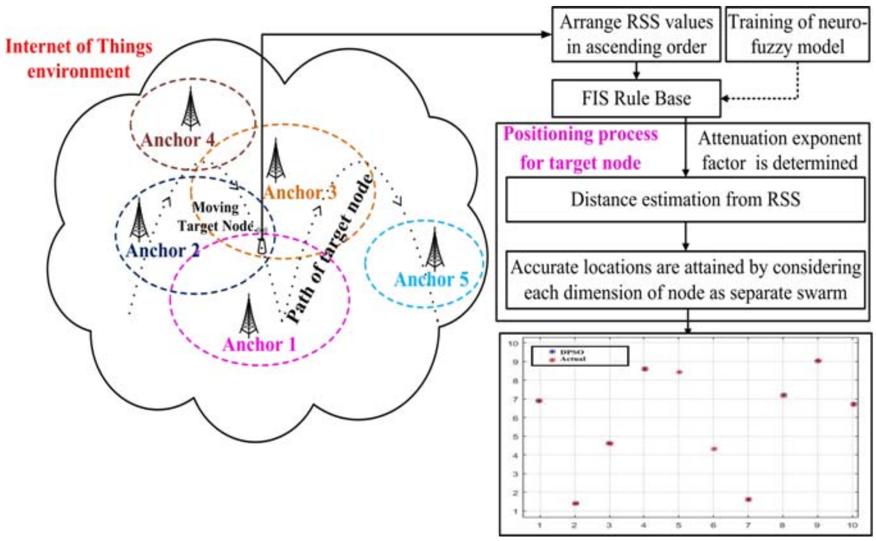


Fig. 1. Outline of the proposed localization process in the environment.

The outline of the proposed technique in the outdoor environment is shown in Fig. 1. The effectiveness of the proposed technique is tested with existing state-of-art methods and three different trajectories are selected for the moving target node. Additionally, ten different localization instances are carried out in environment for the moving target node, which shows the level of accurateness in discrete time intervals. The presented technique is suitable for performing localization in which the nature of nodes may be static or dynamic. The DPSO model consumes minimum energy from the nodes for localization process due to its fast convergence behaviour. Hence, the network has increased lifetime.

The paper is organized as follows. In Section 2, the existing techniques for local-model and DPSO model in localization process. Section 4 portrays the discussions of proposed model with the existing techniques in different paths. In Section 5, conclusions and the future direction of the proposed model are presented.

2. RELATED WORK

The framework that uses data acquiring technologies such as Global Positioning Systems (GPS), infrared sensors, and Radio Frequency Identification (RFID) which are embedded in things is termed as Internet of Things (IoT) [10]. The core concepts of IoT are used in the design phase of cyber-physical systems, military applications, home automation, and warehouse management systems [11]. IoT systems aim to gain the information about the installed nodes such as their location, temperature, and trajectory information [12]. However, the process of identifying the location of moving target nodes has emerged as a major challenge in IOT frameworks.

In recent past, several localization methods have been developed to provide accurate location information in location-aided IoT systems. These methods can be classified based on the measurement techniques either as range-based or range-free, which are used to perform the localization task. The measurement technique utilized for performing the localization task is decided based on the nature of participating nodes [13]. Range based methods consists of Time of Arrival (TOA) method, Time Difference of Arrival (TDOA) method [14], Angle of Arrival (AoA) method [15, 16], and Received Signal Strength Indicator (RSSI) method [17]. Range free methods [18] depend upon the connectivity between anchor and target nodes. In [19], Kalman filters are used for predicting the path of a target node with least-square estimation technique. It is a range free model that avoids the installation of costly external hardware and extends its service by providing inter-node communication. In IOT applications such as vehicle monitoring, forest fire detection, and autonomous gadgets, the target nodes are mobile in nature. So, range-based measurement techniques are more suitable than range-free methods to achieve the domain-specific tasks. RSS follows a simple mathematical method for distance calculation [20] and it is selected as the measurement technology in most of the outdoor setup. In [21], the authors have presented a technique named as Self-adapting Localization for Mobile Nodes (SALMN) and it uses velocity equation and path model equation to track the position of moving target nodes. This method identifies the location of target node based on the path model equation at a defined interval of time. So, it becomes meaningless to determine the location information solely based on the position information in the predecessor localization instance. The proposed model introduces a refined methodology to estimate the position information at each localization instance without considering the previous position estimate values.

Gonzalez-Manzano *et al.* have presented a privacy-preserving aggregation protocol suitable for IoT frameworks, PAgIoT [22]. It is well resistant to security attacks, but the data are aggregated in the absence of spatial information, which may lead to insignificant. Similarly, the authors in [23] have proposed a technique to track the movement of vehicles in urban areas using Extended Kalman filter fitted with partial GPS units. This technique fails to address the energy constraints of network. In [24], the authors have performed localization for a cluster of '*n*' vehicles using a centralized RSS cooperative approach, but the techniques lag in providing accurate location information of all vehicles. So, it has been clearly witnessed that the accuracy of any location estimation model is measured based on the number of target nodes getting localized and the preciseness of produced location information.

Several soft computing techniques namely Particle Swarm Optimization [7, 25], genetic algorithm [26], biogeography based optimization [27], firefly algorithm [28], and Butterfly optimization [29] have been developed by the researchers to produce better results. But, most of the nature inspired algorithms does not work well in resource constrained computational units. In [30], the authors have proposed an improved variant of PSO, named as HPSO, by adding personal best (*pbest*) as an additional parameter in particle update but the objective function does not produce optimal results in all localization tasks. This method fails to fit with the IoT architecture and mobile target nodes. Therefore, DPSO, a variant of PSO is used as the optimization algorithm in the proposed model for attaining exact location information of mobile target node. It also caters the significant role of optimal resource utilization without additional computational overheads. S. Phoemphon *et al.* [31] have used the fuzzy rule set to infer the topology information. Instead, attenuation exponent factor is considered as an important parameter in the proposed technique because the properties of the network vary based on the environmental factors. The proposed model has the following features:

1. In the IoT framework, the moving target node is considered as day to day wearable used by an end user and the anchor nodes are considered as reference points that fall in the path of an end user.
2. The DPSO follows cooperative approach to obtain the position estimate from the global best (*gbest*) results.
3. The computational complexity is reduced because of efficient particle deployment, which is fixed on the basis of 'point of reference' transmission range.

3. PROPOSED METHOD

3.1 Preliminaries

The Received Signal Strength (RSS) values are calculated based on the strength of the signal received by the target node from the anchor nodes. The RSS technique is based on the fact that the radio signal attenuates exponentially with the increase of distance [32]. The RSS values and its corresponding attenuation exponent (α) are considered as primary factors to compute the distance estimate. The attenuation exponent value of each RSS value interprets the real characteristics of the node deployment region and the value of α vary based on the radio irregularities in network. Therefore, the proposed technique concentrates on revealing the actual attenuation exponent value based on fuzzy inference rule base. The adaptive neuro-fuzzy inference system is utilized to frame a neuro-fuzzy model, which undergoes training in the deployment region before the localization process. A set of RSS values is computed between a single target node and randomly deployed anchor nodes. The fuzzy model is fed with the set of RSS values and the training phase is carried out to compute attenuation exponent (α) value. Therefore, the training phase generates a set of valid IF-Then rules. These rules are enforced by the model for selecting the appropriate α value to each RSS value, which are used to calculate the true distance estimate (d_{true}) between the target node and anchor node. The preprocessing steps involved in building the neuro-fuzzy model are discussed in Section 3.2.

Consider a set $A = \{a_1, a_2, \ldots, a_s\}$, that holds s anchor nodes which falls within the transmission range of target node. Let $s = 3$ is considered as Case 1, the DPSO model calculates the centroid position for the co-ordinates belonging to set A. Let $s > 3$ is considered as Case 2, the anchor nodes are sorted based on distance values in ascending order from the target node. The centroid position is calculated for the closest three anchor node co-ordinates belonging to set A. The target node cannot be localized, whenever $s < 3$. The centroid (x_{cent}, y_{cent}) for the three anchor nodes is calculated using Eq. (1).

$$x_{cent} = \frac{\sum_{i=1}^{n} x_i}{n}, y_{cent} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{1}$$

where (x_i, y_i) = Co-ordinate of the ith anchor node.
n = Number of anchor nodes that lie inside the communication range of target node.

Since the distance between participating three anchor nodes and the target node is less than the transmission range (r) of all nodes, the target node will lie within a circular region of radius 'r' with centroid as the origin. The swarm particles are deployed within the circular region, which indirectly reduces the number of iterations taken to achieve global best (*gbest*). The DPSO technique is then applied to the deployed particles to identify the best position that minimizes the cost function, which will be discussed in Section 3.3. The overall architecture of neuro-fuzzy based DPSO localization model is shown in the flowchart in Fig. 2.

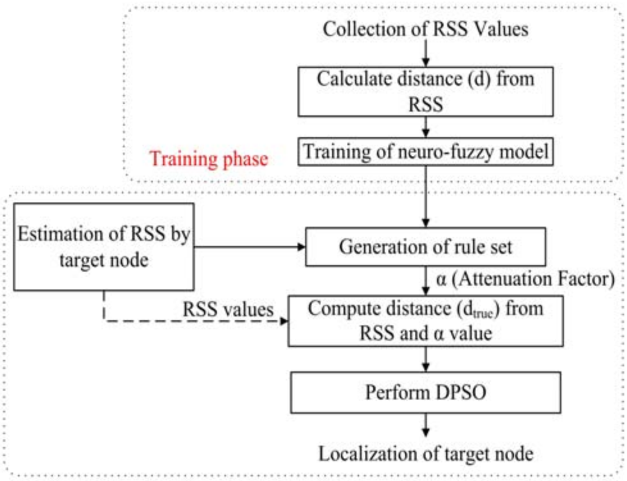


Fig. 2. Overall architecture of neuro-fuzzy based DPSO localization process.

3.2 Adaptive Neuro Fuzzy Inference System

Internet of Things application must act wisely according to the nature of work and geographical location. The characteristics of the network are determined based on the factors such as noise, interference, attenuation exponent, and quality of radio signals. These factors hinder the communication medium in outdoor environments. The proper attenuation exponent value reveals the actual distance information and the process of location identification requires the exact distance estimate for identifying the location of the mobile target node. Hence, the proposed model considers attenuation exponent (α) as a primary factor and the concept of Adaptive Neuro-Fuzzy Inference System (ANFIS) is used to build a strong rule base. The Euclidean distance between the target node and each anchor node is assumed to be known in the simulation environment and the estimated distance is converted into RSS value based on Eq. (2). The anisotropic properties are inhered in the outdoor environments. The dominating parameters namely Degree of Irregularity (DOI) and Gaussian noise are considered in Eq. (2) for estimating the RSS value.

$$RSS = \frac{K}{d_{ij}} - (DOI + Gaussian\ noise) \tag{2}$$

where d_{ij} is the distance between the ith target node and jth anchor node, K is the constant. The value for Degree of Irregularity (DOI) is fixed as 0.01 [30] because in anisotropic networks the dissimilarities in the signal strength are high. DOI is termed as the level of variation in path loss with respect to change of single unit in the direction of signal. The value for Gaussian noise is fixed as 0.02 because the process of location estimation must be robust against the uncertainty of noise.

The training phase is emphasized to overcome the uncertainty of RSS and the nonlinearity between RSS and the distance estimates. The RSS values are fed as input to the neuro-fuzzy model to calculate its respective attenuation exponent (α) and a Fuzzy Inference System (FIS) rule base is concluded from the training phase. The repeated rules present in the rule set are removed and the pruned rule base is framed. The final FIS rule base consists of a valid set of IF-Then rules, as shown in Table 1. The rules are used to create a mapping between inputs and output. This step is applied with the recommendation provided in the recent literature proposed by Gu *et al.* [33] and Amri *et al.* [34]. A normalized RSS input traverses the 5 fuzzy rules (*i.e.*, from five fuzzy RSS inputs to derive five fuzzy attenuation exponent outputs), each of which is applied to the implication method to generate five outputs. The defuzzifier is applied for the fuzzy logic inference and the attenuation exponent factor will be calculated as the derived output. The attenuation exponent for each distance estimate is inversely proportional to the received signal strength (RSS) value. The attenuation exponent is calculated using Eq. (3).

$$\alpha = \frac{\ln(K) - \ln(RSS)}{\ln(d)} \tag{3}$$

In neuro-fuzzy based DPSO localization process, the neuro-fuzzy model takes the input variable as RSS from all the anchor nodes that lie within the transmission range of target node and chooses its respective attenuation exponent (α) values based on the rule base (shown in Table 1). The α value is utilized to compute the true distance estimates of the target node from the anchor node. The true distance estimate (d_{true}) is calculated using Eq. (4).

$$d_{true} = e^{\frac{\ln(K)-\ln(RSS)}{\alpha}} \tag{4}$$

The use of Eqs. (2) and (3) are valid in the proposed model because the training phase and localization process follow the same set of Eqs. (2)-(3). However, in the real-time network scenario, the RSS values are measured using the available hardware to compute its corresponding attenuation exponent values.

Table 1. Rule base of attenuation exponent factors.

S. No.	Antecedent	Consequent
1	If RSS is Vlow, then	Weight of attenuation exponent factor is Vhigh
2	If RSS is Low, then	Weight of attenuation exponent factor is High
3	If RSS is Medium, then	Weight of attenuation exponent factor is Medium
4	If RSS is High, then	Weight of attenuation exponent factor is Low
5	If RSS is Vhigh, then	Weight of attenuation exponent factor is Vlow

3.3 Dimensionality based Particle Swarm Optimization

The mobile nodes exhibit dynamic behavior to achieve its domain-specific goal. In the recent literature, HPSO [30] does not consider the individual dimension of co-ordinate to estimate the position of the unknown node. So, the HPSO method fails to produce accurate position estimates and it consumes more time for convergence. To overcome these drawbacks, the Dimensionality based Particle Swarm optimization (DPSO) method considers each dimension of the co-ordinate separately to localize the moving target node in the search space. It follows a stringent non-increasing objective function in attaining the global best (*gbest*) values of the individual dimension. The proposed model considers the co-ordinate of each node as a *d*-dimensional vector and the individual dimension of each co-ordinate of a node is considered as an individual swarm. The DPSO model splits the *d*-dimensional vector into constituent components as *d* number of 1-D vectors. The fitness evaluation of DPSO is improved by segregating the particles into respective dimension swarms, containing *m* particles each. This drives towards dimension-based optimality.

Algorithm 1 describes the procedure of DPSO localization process. The velocity and position of the particles are updated in each iteration. The position of *i*th particle of swarm *j* is denoted as $D_j.y_i$. $D_j.v_i$ denotes the velocity of *i*th particle in swarm *j*. The velocity and position associated with each particle are updated using Eqs. (5) and (6) respectively.

$$D_j.v_k = \omega D_j.v_k + c_1 r_1 (D_j.p_k - D_j.y_k) + c_2 r_2 (D_j.\hat{g} - D_j.y_k) \tag{5}$$

$$D_j.y_k = D_j.y_k + D_j.v_k \tag{6}$$

The Eq. (6) is dimensionally valid in unit time. $D_j.p_k$ denotes the personal best (*pbest*) of kth particle in jth swarm and $D_j.\hat{g}$ denotes the global best (*gbest*) of jth swarm. The DPSO assigns the values of parameters as stated in Section 4.1 for calculating the exact position of the target node. The parameters namely c_1, c_2, and ω are coined as cognitive, social learning parameters, and inertia weight respectively, which holds a significant role in the convergence properties of DPSO. The population size of particles (m) is fixed as 20 and The uniform random numbers namely r_1, and r_2 are selected in the range of [0,1] for randomizing the attraction in particles. Eberhart and Shi have commended these values for quick convergence in [35] after test runs. The (*gbest*) values of remaining swarms are kept constant while calculating the fitness values of swarm j. This reduces the probability of swarms getting struck into local minima. The DPSO model calculates the objective function based on the Eq. (7).

$$Cost(Y) = \frac{1}{c}\sum_{i=1}^{c} \| E_i - d_{true} \|^2 \tag{7}$$

where, E_i = Estimated distance between particle (position vector Y) and anchor node i. d_{true} = Actual distance calculated from RSS values using the trained fuzzy model.

Each particle is committed to achieve minimum value for the objective function. The position of each particle is updated based on the condition, as shown in Eq. (8).

$$Cost(Y(t)) > Cost(Y(t+1)) \tag{8}$$

The function $func(j, z)$ returns the d-dimensional vector, produced by concatenating all the *gbest* vectors across all swarms[$D_1.\hat{g}$, $D_2.\hat{g}$, z, …, $D_j.\hat{g}$, …, $D_d.\hat{g}$], where z represents the position of any particle from swarm j, until $j = d$. The resultant vector is obtained by consolidating the global best values of all dimensions. The co-ordinate positions are directly consequential from the resultant vector. Hence, the co-ordinates of the target node are estimated with high accuracy in each dimension of the solution space.

The DPSO algorithm consumes Δs time to finish the localization task, but the target node must have moved in its path during this time interval. So, in addition to DPSO localization, the proposed method uses the velocity and path information of nodes to compute the current position of the target node. This helps the network administrator to find the node information accurately. The localization process starts at time t. Suppose at time t, the velocity of the target node is v_t, the direction angle is θ_t, the location obtained from DPSO is (x_t, y_t), the location of the target node after Δs time is denoted as (x_{acc}, y_{acc}).

The position of target node is calculated at each Δt time intervals. The current position of the target node is calculated using Eq. (9).

$$x_{acc} = x_t + v_t * \Delta s * \Delta\cos\,\theta_t,\ y_{acc} = y_t + v_t * \Delta s * \Delta\sin\,\theta_t \tag{9}$$

At time t, the velocity v_t and direction angle θ_t are calculated using the Eqs. (10) and (11) respectively.

$$v_t = \frac{\sqrt{(x_{(t-1)} - x_t)^2 + (y_{(t-1)} - y_t)^2}}{\Delta t + \Delta s} \tag{10}$$

$$\theta_t = \begin{cases} \arctan\dfrac{y_t - y_{(t-1)}}{x_t - x_{(t-1)}}, & \text{if } x_t - x_{(t-1)} \geq 0 \\ \pi + \arctan\dfrac{y_t - y_{(t-1)}}{x_t - x_{(t-1)}}, & \text{if } x_t - x_{(t-1)} < 0 \end{cases} \tag{11}$$

where $(x_{(t-1)}, y_{(t-1)})$ is the location of the target node at time $t - 1$.

Algorithm 1: DPSO algorithm

procedure *DPSO*
  $func(j, z) \equiv [D_1.\hat{g}, D_2.\hat{g}, \ldots, D_{j-1}.\hat{g}, z, D_{j+1}.\hat{g}, \ldots, D_n.\hat{g}]$
  $PSO_j, j \in [1\ldots n]$
  repeat
  for each swarm $j \in [1\ldots n]$ **do**
    for each particle k in swarm j **do**
      if $cost(func(j, D_j.y_k)) < cost(func(j, D_j.p_k))$ **then**
        $D_j.p_k = D_j.y_k$
      end if
      if $cost(func(j, D_j.p_k)) < cost(func(j, D_j.\hat{g}))$ **then**
        $D_j.\hat{g} = D_j.p_k$
      end if
      Perform *PSO* updates on PSO_j using Eqs. (5) and (6)
    end for
  end for
  Until Stopping condition is true
end procedure

4. EXPERIMENTS AND RESULTS

In this paper, the presented algorithm, DPSO is tested with the existing algorithms such as PSO and HPSO. It is assumed that the target node moves along a path and this node is localized at various instances with the help of the anchor nodes that lie within its transmission range. Initially, the anchor nodes are deployed randomly in a [10×10] grid. In order to mimic the IoT framework scenario into simulation environment, the target nodes are allowed to move in random manner within the specified boundary. Then, three paths are chosen randomly for the movement of target node to evaluate the performance of the DPSO model. This increases the complexity of the overall system. The DPSO technique is tested with a moving target node along three different paths with randomly deployed sixty anchor nodes in the simulation environment and the results are captured using a MATLAB simulator. The results produced by the DPSO model are compared with the existing techniques (PSO and HPSO) for three different paths. The presented model outperforms well in terms of performance metrics such as node estimation error, average node localization error, average localization error rate and number of iterations required for convergence. The efficiency of the presented technique is judged based on these performance metrics and the three trajectories of the target node are given as Eqs.

(12)-(14) respectively.

$$y = 10 * (1 - e^{-5}) * (1 - e^{-0.5x}) \tag{12}$$

$$y = abs(9 * cos(0.7x)) \tag{13}$$

$$y = 65 * \left(\left(\tfrac{x}{10} - 1 \right)^3 + \left(\tfrac{x}{10} - 1 \right)^2 \right) \tag{14}$$

4.1 DPSO Parameters

The DPSO considers the parameters stated in Table 2 for evaluating the exact target node positions. The parameters are fixed by DPSO according to [7, 36] as:

Table 2. Different parameters used in DPSO.

Parameter	Value
Maximum number of iterations	50
Population size of particles in each swarm (m)	20
Inertia weight (w) [36]	0.729
Cognitive learning parameter (c_1) [36] Social learning	1.494
parameter (c_2) [36]	1.494
In 2D search space, the swarm size (d)	2
Number of trials	30

The number of iterations is fixed as 50 because the increase in number of iterations does not guarantee significant enhancement in performance factor. The population size of particles (m) is fixed as 20 and the number of swarms (d) is fixed as 2 in the search space. The value of inertia weight (ω), cognitive learning parameter (c_1), and social learning parameter (c_2) are motivated after experimental tests [7, 36]. This drives to fast convergence and the existing literature also used these values for performing the localization process.

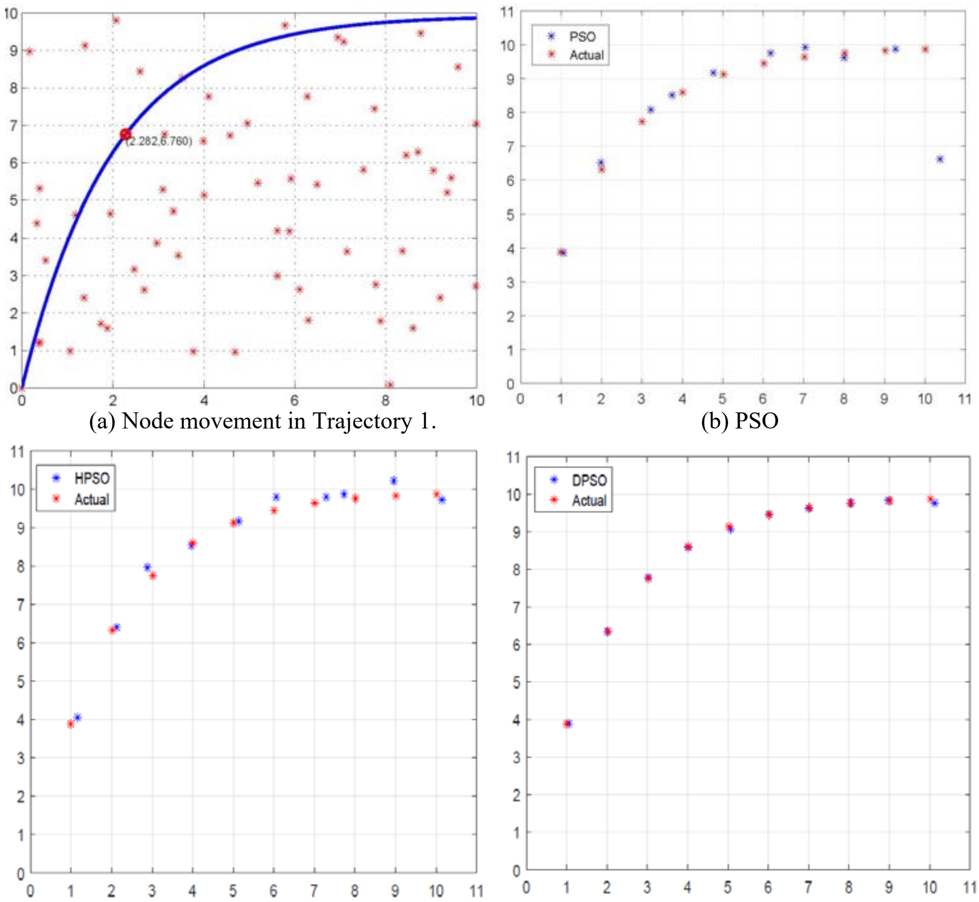
4.2 Node Estimation Error

The difference between the actual location of target node and the estimated location is calculated using Eq. (15).

$$NEE = \sqrt{(x_{est} - x_{act})^2 + (y_{est} - y_{act})^2} \tag{15}$$

where (x_{est}, y_{est}) = Estimated coordinates of target node.
(x_{act}, y_{act}) = Actual position of target node.

In the 2-D [10×10] environment, sixty nodes are randomly deployed for three different test cases consisting of three different paths. The number of anchor nodes are fixed as sixty because of the randomness involved in the initial node deployment phase, which leads to more anchors being deployed in a same region. But, the density of anchor nodes will be significantly reduced in the real time environment based on the context of the application. The location information of the moving target node is estimated in ten

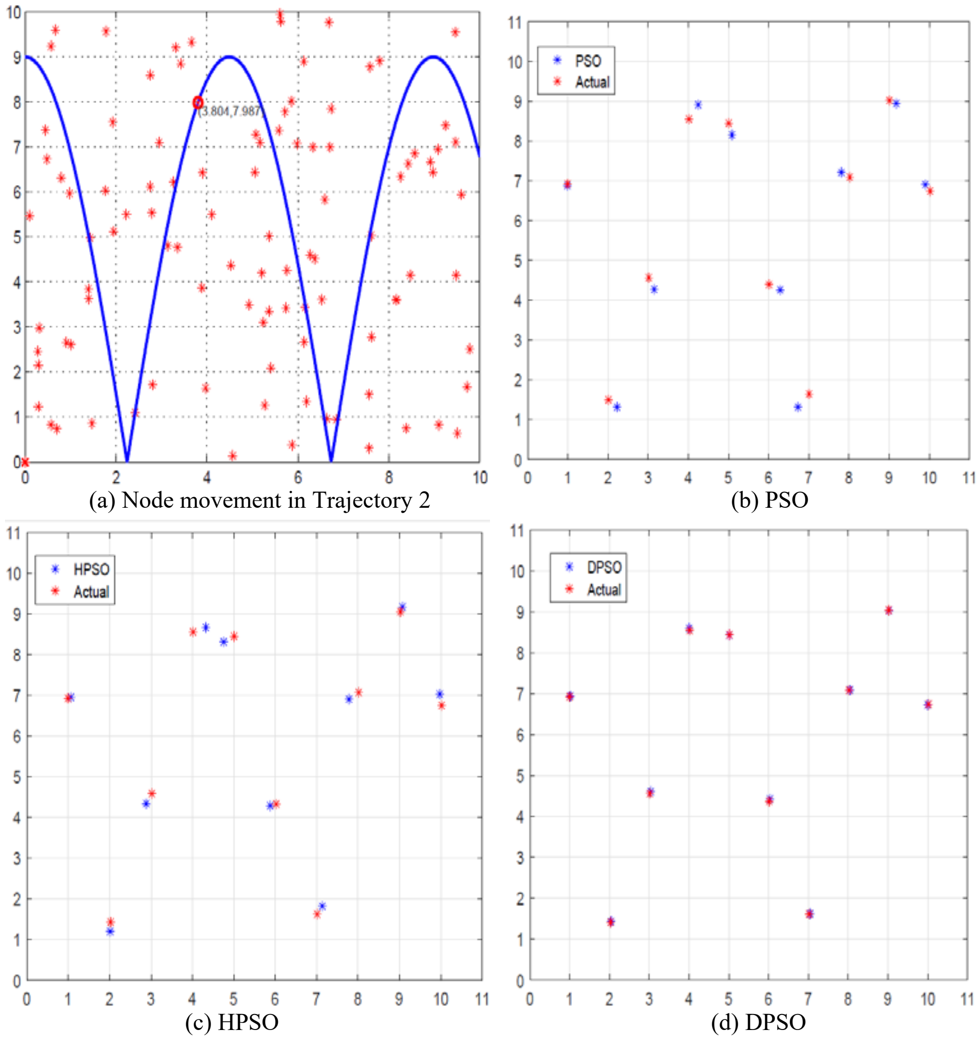


(a) Node movement in Trajectory 1. (b) PSO

(c) HPSO (d) DPSO

Fig. 3. Results of Localization process for Trajectory 1.

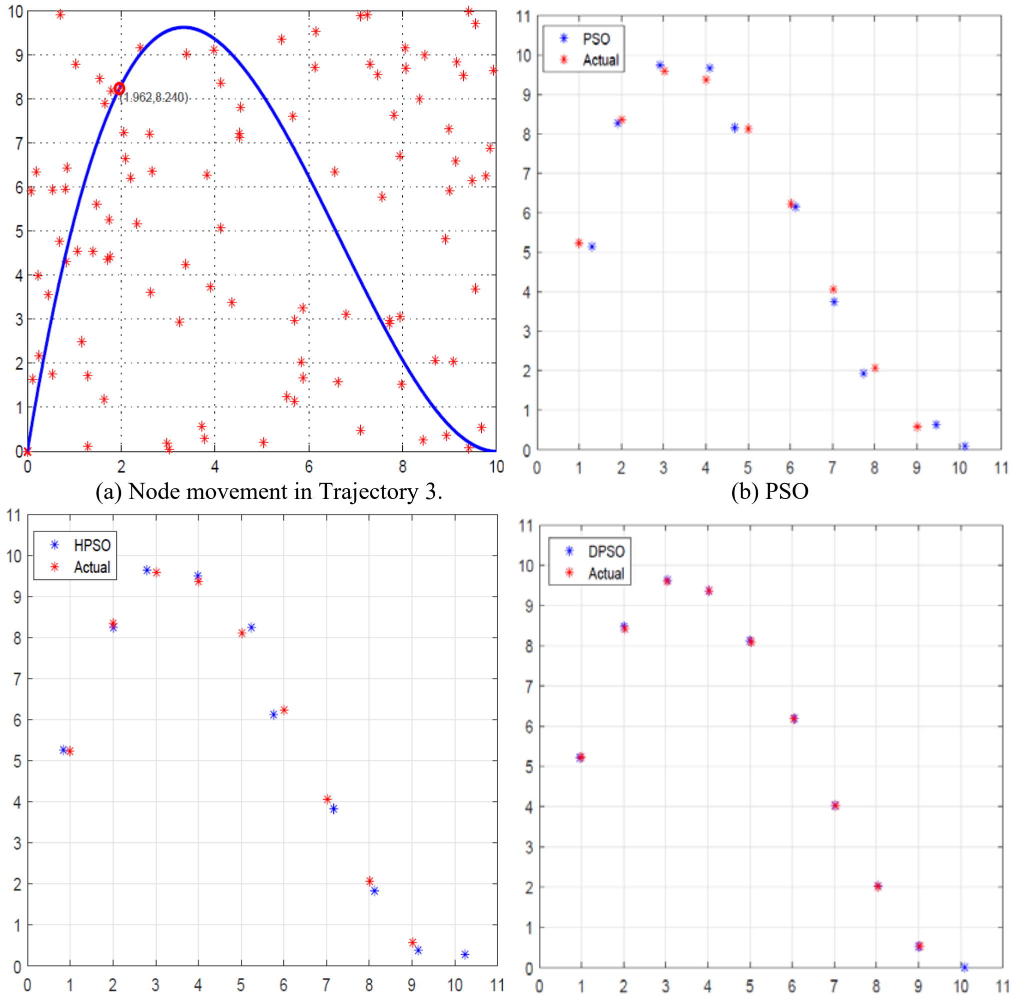
instances for each test case. Fig. 3 (a) shows the path of target node, as stated in Eq. (12) and the initial random deployment of anchor nodes. Figs. 3 (b) and (c) show the spatial representation of the actual position of the target node and the estimated positions calculated by PSO [25] and HPSO [30] respectively. Fig. 3 (d) shows the representation of actual position and the estimated position computed by DPSO. It produces accurate results for ten discrete instances. The proposed method contains a significant increase in accurateness compared with the other methods, as well as considerable improvement over HPSO [30], which are achieved due to the training of neuro-fuzzy model to identify the attenuation exponent value. The proposed method is also tested with two randomly chosen paths to test the true characteristics such as reliability, robustness, and degree of adaptability. Fig. 4 (a) shows the scenario with sixty anchor nodes and another trajectory of the target node, as stated in Eq. (13). Figs. 4 (b) and (c) display the representation of the position of the target node and the estimated positions by PSO and HPSO respectively. The location information calculated by the existing methods are imprecise in nine instances out of ten while the DPSO technique identifies the exact location of the moving target in all the ten instances, as shown in Fig. 4 (d). In Fig. 5 (a), the anchor node deployment and the path for target node movement, as stated in Eq. (14) are shown. The position estimated by PSO and HPSO [30] technique for different instances along the trajectory are shown in Figs. 5 (b) and (c) respectively. Although HPSO [30] performs well compared with the PSO, the estimation process fails to calculate the accurate location for each dimension of the target node. The HPSO calculates the gbest value in the overall swarm while DPSO calculates gbest value in each dimension (*i.e.*, each dimension of target node co-ordinate is considered as a single swarm). This results in producing optimized results which can be viewed in Fig. 5 (d). The location information of target node is identified in all the ten instances with 97.5% accuracy.



(a) Node movement in Trajectory 2 (b) PSO

(c) HPSO (d) DPSO

Fig. 4. Results of Localization process for Trajectory 2.



(a) Node movement in Trajectory 3. (b) PSO

(c) HPSO (d) DPSO

Fig. 5. Results of Localization process for Trajectory 3.

4.3 Localization Error

In Table 3, the computed results of PSO, HPSO, and DPSO are tabulated in terms of maximum localization error, average localization error, and minimum localization error. From Table 3, it can be witnessed that the DPSO model delivers high accuracy by computing minimum localization error compared with the PSO and HPSO techniques. DPSO delivers the high accuracy rate because of concentrating in individual dimension of target node. The average localization error is considered as a performance metric for evaluating the efficiency of localization models, which is calculated by averaging the error results after repeated test runs over the three trajectories. The average localization error included with minimum and maximum localization error are nominated as standard indices for performance evaluation and are followed in the recent literature [13, 37].

Table 3. Comparison between PSO, HPSO, and DPSO in terms of localization error.

Trajectory of Target node	Method	Max. Localization Error (m)	Min. Localization Error (m)	Avg. Localization Error (m)
Traj. 1 (as in Eqn. 12)	PSO	0.4454	0.066	0.2026
	HPSO	0.3342	0.1556	0.2682
	DPSO	0.0727	0.0141	0.0317
Traj.2 (as in Eqn. 13)	PSO	0.4959	0.1919	0.3385
	HPSO	0.3217	0.0183	0.1839
	DPSO	0.0622	0.010	0.0319
Traj. 3 (as in Eqn. 14)	PSO	0.4297	0.0659	0.2640
	HPSO	0.3476	0.0665	0.1992
	DPSO	0.0557	0.006	0.0301

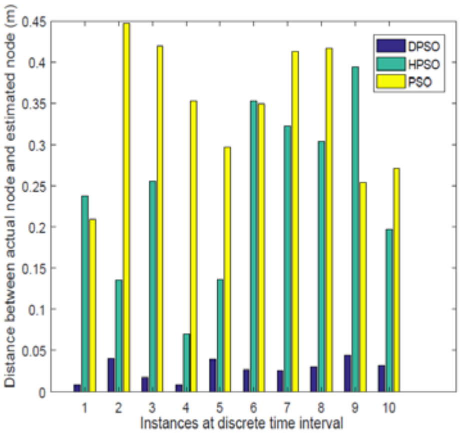
4.4 Target Nodes vs. Estimated Accuracy

The location error is computed for ten instances in the localization process of a moving target node. The target node triggers different nodes as their neighbourhood anchor nodes at each localization instance because of its randomly chosen path. In Table 4, the average localization error rate computed by DPSO is compared with the HPSO and PSO technique. The error rate is calculated for each path contained of 30 independent trials, averaged together. The proposed technique contains a notable edge in accuracy in comparison to the PSO as well as a significant lead over HPSO [30]. This is achieved by the neuro-fuzzy training of RSS values, which enhances the robustness of the system.

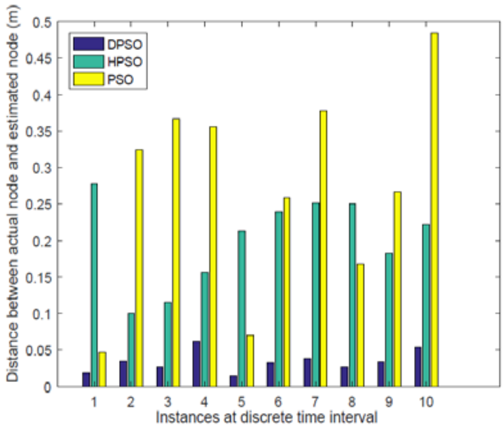
Table 4. Summary of 30 trial runs of PSO, HPSO and DPSO in terms of average localization error rate.

Trajectory of Target node	Method	Average Localization Error rate
Trajectory 1 (as in Eq. (12))	PSO	1.3192
	HPSO	0.4835
	DPSO	0.1272
Trajectory 2 (as in Eq. (13))	PSO	1.4026
	HPSO	0.5631
	DPSO	0.1317
Trajectory 3 (as in Eq. (14))	PSO	1.2853
	HPSO	0.4451
	DPSO	0.1193

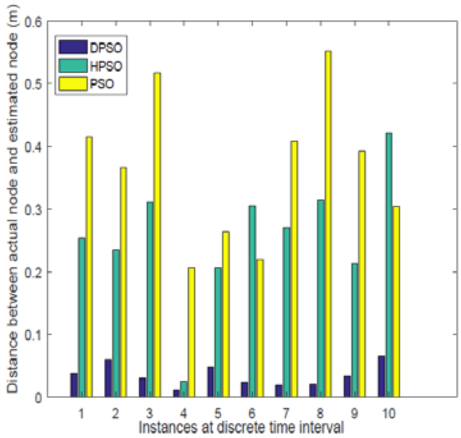
Fig. 6 (a), shows the comparison of the location error for the target node by PSO, HPSO, and DPSO for all instances in the path (as in Eqs. (1)-(2)). In DPSO localization process, the location error is minimum for all the instances because Δs time (*i.e.*, time taken to finish the location identification process) is considered for computing the final position estimate of target node at each instance. The number of localization instances is restricted to 10 because of stringent constraints over energy consumption of target node. So, the DPSO technique concentrates to minimize the error between the estimated position of the target node and its actual position in all instances. In order to showcase the effectiveness of the proposed model, the location error is computed with PSO, HPSO, and DPSO for another path (as in Eq. (13)) with randomly deployed anchor nodes. The comparisons were done for each localization instance of the target node, which is shown in Fig. 6 (b). Fig. 6 (c) shows the comparison of the location error for the target node by PSO, HPSO, and DPSO for all instances in the path (as in Eq. (14)). The location error witnessed by the DPSO model is less for all the localization instances.



(a) Trajectory 1.



(b) Trajectory 2.



(c) Trajectory 3.

Fig. 6. Comparison between PSO, HPSO, and DPSO in terms of location error.

4.5 Effectiveness of Minimized Iterations

The number of iterations required for attaining mature convergence determines the computational complexity of the overall system. The maximum number of iterations is restricted to 50 in DPSO model and this value is fixed after testing algorithm with various test case deployments. In the localization process of the target node over ten instances, the consolidated results are shown in Fig. 7 (a). It can be clearly witnessed that the DPSO model requires less number of iterations to identify the location of target node at each instance in its path (as in Eq. (12)) compared with existing techniques such as PSO and HPSO. So, the reduction in number of iterations leads to optimal utilization of energy from the resource-constrained network. The number of iterations taken by DPSO is compared with the PSO and HPSO techniques for the other two paths (as in Eqs. (13) and (14)) are shown in Figs. 7 (b) and (c) respectively.

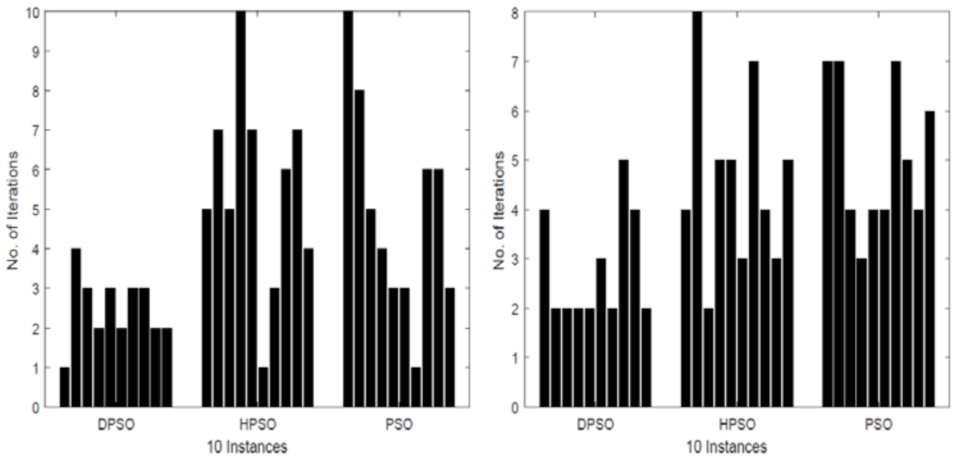


Fig. 7. Comparison chart between the techniques PSO, HPSO, and DPSO.

Fig. 7 (d) shows the maximum number of iterations taken by any single target node in the localization process of different node population such as 100 targets, 120 targets, 140 targets, 160 targets, 180 targets and 200 targets. The DPSO model is compared with the existing techniques such as PSO and HPSO [30] for a single instance in the path (as in Eq. (12)). From Fig. 7 (d), it can be clearly witnessed that the global best (*gbest*) is achieved in minimum number of iterations.

5. CONCLUSION AND FUTURE WORK

In this paper, we have presented a technique named as Dimensionality based optimization technique to reveal the exact position of the moving node. The two main contributions are adaptive neuro-fuzzy based inference engine and dimension pruned location discovery model. The fuzzy model explores the true characteristics of the present environment by calculating the exact attenuation factor (α) based on the RSS estimate and reduces the computational complexity involved in localization task. This also reveals the true distance estimate for the position estimation process since the strong rule base mimics the network behaviour present in any installation environment. The location of the target node is calculated in ten instances and the path is randomly chosen depending on the geographical scene. The DPSO model identifies the exact location, which also ensures the network administrator by producing precise location information for each dimension of the co-ordinate of the target node. These optimized results are achieved due to critical IF-Then rules generated by ANFIS engine, which is also accompanied by a dimension based swarm formation step followed by DPSO model for particle deployment. The proposed model ensures appreciable performance standards by addressing the on-field complexities of IoT such as energy utilization, network lifetime, and environmental factors. Therefore, an efficient localization model is proposed for estimating the location of moving target node in wireless communication spectrum with high accuracy.

Future work will investigate on extending the proposed model using range free measurement technologies. This will reduce the cost and the extra hardware inculcated in the localization process and it can be implemented using Field-Programmable Gate Array (FPGA). This field-programmable integrated chip is employed to monitor the on-field complexities in the context of the application.

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