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HYBRID FUZZY NEURAL NETWORK (HFNN) BASED MODEL FOR THE PREDICTION OF NODE LOCALIZATION

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Abstract: Node Localization is a fundamental issue for many critical applications in Wireless sensor networks (WSNs). It is a process in which we estimate the coordinates of the unknown nodes using sensors with known coordinates called anchor nodes. WSN localization problem is formulated as an NP-Hard optimization problem because of its size and complexity. In this research work, proposed an efficient way to evaluate the optimal network parameters that result in low Average Localisation Error (ALE) using a machine learning approach based on Hybrid Fuzzy Neural network (HFNN) and the optimization is done using the Enhanced Lion Optimization algorithm (ELO). An error model is described for estimation of optimal node location in a manner such that the location error is minimized using HFNN and ELO algorithms. The proposed HFNN and ELO algorithms are matured to optimize the sensors' locations and perform better as compared to the existing optimization algorithms. The simulation is done using the NS-2 tool for analyzing the efficient performance in wireless sensor networks.

Keywords: Node Localization, Average Localisation Error (ALE), Hybrid Fuzzy Neural network (HFNN), Enhanced Lion Optimization algorithm (ELO).

1. Introduction

In recent years, with rapid advances in Micro Electro Mechanical Systems (MEMS) technology, research on Wireless Sensor Networks (WSNs) has received extensive interest. It is getting popular due to its low cost and small size and its applications in military and civilian surveillance. However, wireless sensor networks have a few inherent limitations. e.g., limited hardware, limited transmission range, and large scale network system and the traditional protocols or mechanisms cannot use in WSNs. Hence, several issues are needed to consider in WSNs to construct an efficient and robust network. For example, sensor nodes have limited computation capability and limited power supply, and therefore low complexity algorithms and power saving schemes should be designed.

In wireless sensor networks, localization of nodes plays an important role in most of the applications. When sensors are deployed over a network, normally they have only connectivity information with their neighbors, without knowing their own location information. In some situations, the problem can have easy solution if location information of the nodes is available.

For example, routing path can be constructed easily, and coverage hole can easily be detected, if nodes have location information. Knowing relative location of sensors allows the location-based addressing and routing protocols, which can improve network robustness and energy-efficiency effectively. Recent research results show that nodes with location information lead to increased performance of applications and reduced power consumption. In addition, more accurate location information leads to the more accurate result that application needs. In summary, localization is an essential part of WSNs.

Localization in wireless sensor networks is different from the traditional wireless communication technology. It is an important aspect in WSNs as the events detected by sensors usually should contain location of those nodes that detect a target. For example, location of a military tank should be informed to the sink if it is detected by the sensors, which can be achieved through location information of the sensors. Besides, many network operations also depend on the locations of sensors, such as geographic routing, key distribution protocols, and location-based authentication. Incorrect locations may lead to severe consequences. For example, lack of location information of sensors may lead to wrong military decisions on the battlefield and falsely granting access rights to people. Thus it is important and essential to ensure the correctness of sensors' locations. There has been an increasing interest in the localization techniques for WSNs in recent years and many localization algorithms have been proposed. Constraint on limited hardware supports and power supply, sensor nodes can only find its approximate location information. In order to find node's location effectively, various localization algorithms are proposed, which can be further classified into *range-based* and *range-free* localization schemes. The range-based localization scheme uses measurements of distance or angle to estimate the node's location. According to signal propagation and receive time, two kinds of technology are mentioned to obtain the distance. They are: time of arrival (TOA), time of difference of arrival (TODA). TOA method is used to obtain the range between the sender and receiver nodes by signal arrival time. TODA technique is based on the difference in time between two different signals arrival time and is widely proposed as a necessary measurement method in localization solution for WSNs.

2. Literature Review

In this section reviews the some of the recent techniques for the detection of node localization using computational intelligence in wireless sensor networks.

Costa et al [12] introduced a scalable, distributed weighted-multidimensional scaling (dwMDS) algorithm that adaptively emphasizes the most accurate range measurements and naturally accounts for communication constraints within the sensor network. Each node adaptively chooses a neighborhood of sensors, updates its position estimate by minimizing a local cost function and then passes this update to neighboring sensors. Derived bounds on communication requirements provide insight on the energy efficiency of the proposed distributed method versus a centralized approach. For received signal-strength (RSS) based range measurements, we demonstrate via simulation that location estimates are nearly unbiased with variance close to the Cramér-Rao lower bound. Further, RSS and time-of-arrival (TOA) channel measurements are used to demonstrate performance as good as the centralized maximum-likelihood estimator (MLE) in a real-world sensor network.

Wang et al [13] proposed a new approach to the localization problem in wireless sensor networks using received-signal-strength (RSS) measurements. The problem is reformulated under the equivalent exponential transformation of the conventional path loss measurement model and the unscented transformation (UT), and is approximately approached by the maximum likelihood (ML) parameter estimation, which we refer to as the weighted least squares (WLS) approach. This formulation is used for sensor node localization in both noncooperative and cooperative scenarios. Simulation results confirm the effectiveness of the approach for both outdoor and indoor environments.

Sahoo et al [14] proposed a novel localization algorithms to find out possible location information of the normal nodes in a collaborative manner for an outdoor environment with help of few beacons and anchor nodes. In our localization scheme, at most three beacon nodes should be collaborated to find out the accurate location information of any normal node. Besides, analytical methods are designed to calculate and reduce the localization error using probability distribution function. Performance evaluation of our algorithm shows that there is a tradeoff between deployed number of beacon nodes and localization error, and average localization time of the network can be increased with increase in the number of normal nodes deployed over a region.

Bao et al [15] developed a particle swarm optimization (PSO) based localization algorithm (PLA) for WSNs with one or more mobile anchors. In PLA, each mobile anchor broadcasts beacons periodically, and sensor nodes locate themselves upon the receipt of multiple such messages. PLA does not require anchors to move along an optimized or a pre-determined path. This property makes it suitable for WSN applications in which data-collection and network management are undertaken by mobile data sinks with known locations. To the best of our knowledge, this is the first time that PSO is used in range-free localization in a WSN with mobile anchors. We further derive the upper bound on the localization error using Centroid method and PLA. Simulation results show that PLA can achieve high performance in various scenarios.

Gong-qian et al [16] proposed a DV-Hop algorithm based on the error bound (EBDV-Hop) for the problems of DV-Hop that node localization algorithm caused by estimating large distance, and the problem of particle swarm optimization algorithm to search a large space and solve the problems slowly: Firstly EBDV-Hop model is set up based on the analysis algorithm error of DV-Hop; Then the positioning results are optimized by improved particle swarm optimization clustering which is proposed based on model; EBDV-Hop and DV-Hop are simulated in situation in following situations including in different anchors, different communication radius and different iteration number. The results show that EBDV-Hop can improve the positioning accuracy and positioning speed effectively.

Basaran et al [17] presented a centralized, range- and anchor-based, hybrid algorithm called RH+ that aims to combine the powerful features of two orthogonal techniques: Classical Multi-Dimensional Scaling (CMDS) and Particle Spring Optimization (PSO). As a result, we find that our hybrid approach gives a fast-converging solution which is resilient to range-errors and very robust to topology changes. Across all topologies we studied, the average estimation error is less than 0.5 m. when the average node density is 10 and only 2.5% of the nodes are beacons.

Chen et al [18] proposed a range-free cooperative localization algorithm for mobile sensor networks by combining hop-distance measurements with particle filtering. In the hop-distance measurement step, we design a differential-error correction scheme to reduce the positioning error accumulated over multiple hops. We also introduce a backoff-based broadcast mechanism in our localization algorithm. It efficiently suppresses redundant broadcasts and reduces message overhead. The proposed localization method has fast convergence with small location estimation error. We verify our algorithm in various scenarios and compare it with conventional localization methods. Simulation results show that our proposed method has similar or superior performance when compared to other state-of-the-art localization algorithms.

Kuang et al [19] proposed a new distributed node localization algorithm named mobile beacons–improved particle filter (MB-IPF). In the algorithm, the mobile nodes equipped with globe position system (GPS) move around in the wireless sensor network (WSN) field based on the Gauss-Markov mobility model, and periodically broadcast the beacon messages. Each unknown node estimates its location in a fully distributed mode based on the received mobile beacons. The localization algorithm is based on the IPF and several refinements, including the proposed weighted centroid algorithm, the residual resampling algorithm, and the markov chain monte carlo (MCMC) method etc., which were also introduced for performance improvement. The simulation results show that our proposed algorithm is efficient for most applications.

Gumaida et al [20] presented a modern and high-efficiency algorithm based on a new optimization technique for localization processes in an outdoor environment. The new optimization technique combines particle swarm optimization (PSO) with variable neighborhood search (VNS) and is called hybrid particle swarm optimization with variable neighborhood search (HPSOVNS). The objective function, which utilized by HPSOVNS for optimization, is the last mean squared range error of all neighboring anchor nodes. The interior distances between WSN nodes are calculated using a received signal strength indicator (RSSI) function. HPSOVNS is a hybrid optimization technique showing elevated performance in finding the best solution that rapidly affirms the minimization of an objective function without being stuck in local optima. The proposed algorithm can increase localization accuracy because it combines the positive features and effective capabilities of PSO and VNS with RSSI.

Gao et al [21] developed a WSN localization algorithm based on adaptive particle swarm optimization (APSO) was put forward in combination with particle swarm theory and DV-Hop algorithm. This algorithm improved localization precision by more than 20%, and the effect of node density on localization precision was significantly less than DV-Hop algorithm without any addition of hardware facilities and communication load.

Singh et al [22] proposed an efficient way to evaluate the optimal network parameters that result in low Average Localisation Error (ALE) using a machine learning approach based on Support Vector Regression (SVR) model. We have proposed three methods (S-SVR, Z-SVR and R-SVR) based on feature standardisation for fast and accurate prediction of ALE. We have considered the anchor ratio, transmission range, node density and iterations as features for training and prediction of ALE. These feature values are extracted from the modified Cuckoo Search (CS) simulations. In doing so, we found that all the methods perform exceptionally well with method R-SVR outperforming the other two methods with a correlation coefficient (R = 0.82) and Root Mean Square Error (RMSE = 0.147m).

3. Proposed Methodology

In this research work, proposed an efficient way to evaluate the optimal network parameters that result in low Average Localisation Error (ALE) using a machine learning approach based on Hybrid Fuzzy Neural network (HFNN) and the optimization is done using the Enhanced Lion Optimization algorithm (ELO). An error model is described for estimation of optimal node location in a manner such that the location error is minimized using HFNN and ELO algorithms. The proposed HFNN and ELO algorithms are matured to optimize the sensors' locations and perform better as compared to the existing optimization algorithms.

3.1. SYSTEM MODEL

In this section, first, we have discussed the system architecture designed for the node localisation process. Then we have discussed the method to compute the distance between the anchor and unknown nodes. Afterwards, we have discussed the objective function formation and working of the modified CS algorithm for node localisation. Finally, we have discussed the details of the machine learning model used.

A. SYSTEM ARCHITECTURE

The sensor nodes are considered to be deployed randomly inside a region with area *X* _ *Y* square units. The system consists of *M* anchor nodes. These anchor nodes act as a reference for all *N* unknown nodes of the network, which need to be localised. All the sensors can transmit/receive data within a transmission range of *R* distance units. The anchor's positional information is utilised as a reference to evaluate the coordinates of all the localisable unknown nodes. An unknown node is considered localisable only if it has at the minimum three anchor nodes inside its communication range.

DISTANCE CALCULATION AND OPTIMISATION

Problem Formation

The RSSI is used by the unknown nodes to calculate their distances from the anchor nodes. Sensors experience a power loss during the exchange of information because of shadowing and multipath fading. This path loss is modelled as log-normal shadowing [27], which is expressed as shown in Eq.(1):

$$PL(d) = PL_0 + 10 \times \eta \times log_{10}\left(\frac{d}{d_0}\right) + X_g$$

In Eq.(1), $PL(d)$, PL_0, and *d* represent total path loss (transmitted power _ received power), path loss at a reference distance *d*0, and the distance between the transmitter and the receiver respectively. Besides, _ denotes the path loss exponent showing how the strength of the received signal decreases with the increase in distance between transmitter and receiver. The value of _ relies on various parameters such as signal frequency, antenna height, and the propagation environment. Generally, the value of _ lies in the range of 2-6 [29] and is higher than 4 for indoor or shadowed environment. Furthermore, _ represents the standard deviation of shadowing effects, and its value varies with the signal propagation environment and is generally higher than 4 dB [31]. *Xg* is a Gaussian random value representing the attenuation caused by fading.

A ranging error is experienced as the result of log-normal shadowing. This ranging error observes a zero-mean Gaussian distribution. Its variance _2 is expressed in Eq.(2):

$$\sigma^2 = \gamma^2 \times D_{ij}^2$$

where, represents the localisation error between the actual and measured Euclidean distance *Dij* between *ith* node (*xi*; *yi*) and the *jth* node (*xj*; *yj*) and is known as Gaussian noise having mean zero and standard deviation one. We have considered the value of equal to 0.1 as it is the most appropriate value used in literature [20], [32]. Eq. (2) shows that the standard deviation of the ranging error varies linearly with the actual distance between two nodes. The real distance *Dij* can be calculated using the following Eq.(3):

$$D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

A circular disk model has been adopted to establish network connectivity: two nodes *i* and *j* can converse with each other only if *Dij* 6 *R*, where *R* is the transmission range of both the sensor nodes. The measured distance is represented by *D*0*ij*, and is given by the expression in Eq.(4):

$$D'_{ij} = D_{ij} + N_{ij}$$

where, *Nij* is the ranging error between node *i* and *j*. While calculating the position of the unknown nodes, there always exists a ranging error. So, we need to evaluate the position of the unknown nodes as precisely as possible, considering this inevitable ranging error. To achieve this, we formulate an Optimisation Function (OF), which is the mean of the square of the error between the actual distance of evaluated node coordinates and the estimated distance of actual unknown node coordinates from the neighbouring anchor nodes. Let, (*xi*; *yi*) and (*xj*; *yj*) be the position of *ith* unknown node and *jth* anchor node respectively. The OF is given in Eq.(5):

$$OF(x_i - y_i) = \frac{1}{M} \times \sum_{j=1}^{M} (D_{ij} - D'_{ij})^2$$

where, *M* > 3, because an unknown node should have at the minimum three anchor nodes within its transmission range to be considered as localisable (trilateration rule). The (*xi*; *yi*) corresponding to the minimum value of the OF is the evaluated position of the unknown node.

Hybrid Fuzzy Neural Network

The Fuzzy neural network is the fusion of ANN and fuzzy logic. These networks have become popular as the output generated is not crisp but fuzzy. Due to this, the partial belonging to a particular class helps in better classification. The fuzzy membership value and the operations on the fuzzy set play an important role in the working of fuzzy neural networks. In view of the benefits of fuzzy logic and ANN, a fuzzy neural network (FNN) was proposed for classification. FNN is based on the accumulation of fuzzy hyperboxes. FMNN training is done by creating hyperboxes belonging to different classes. The training algorithm has two parts: expansion and contraction. During the expansion process, the size of the hyperboxes is decided by the expansion coefficient. The contraction process removes the overlap between other class hyperboxes [6]. Later this concept was to construct the hyperboxes using labeled and unlabeled data. The fuzzy neural network with a compensatory neuron (FMCN) is proposed by Nandedkar and Biswas. To increase the accuracy of FMNN many learning algorithms and new architectures [9], [10], [11], [12] have been proposed. The drawback of these networks is the effect of the parameters adjusting the size, expansion and contraction process along with the overlap test. Apart from this many other clustering algorithms were proposed by various researchers which include fuzzy clustering [13], [14], [15], [16], [17], [18], [19], [20], [21] for constructing the RBFNN hidden layer. The proposed FNN is the extension of [22] which uses the pruning algorithm [23] after fuzzy clustering to optimize the neurons in the hidden layer, and fuzzy union operation to find the output of the network. This classifier provides an improvement in earlier classifiers. The rest of the paper is organized as follows. The following section 2 gives the introduction of RBFNN in brief along with the clustering algorithms suggested by different researchers. Section 3 describes the architecture and learning of the FNN. In section 4 experimental results with different case studies have been discussed. Lastly, section 5 provides the conclusion and also the future scope.

Fuzzy neural network architecture and learning Algorithm The architecture of the fuzzy neural network is shown in Fig. 2. As shown, the connection between the input layer to the hidden layer is fully connected. The output of each hidden neuron or FSH is determined by a fuzzy membership function. As seen from Fig. 2, there is the partial connection between output and hidden layer since the FSHs created during clustering for that class are only connected to the class node. The output of the class node is determined by the fuzzy union operation.

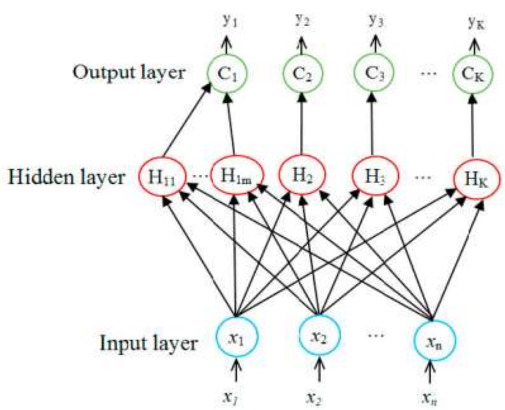


Fig. 2. Fuzzy Neural Network From Fig. 2, it is observed that class 1 has m number of clusters while other classes are having only one cluster, which may vary in accordance with the application. The training of proposed architecture consist of two steps: a) Creating FSH in the hidden layer of FNN by performing fuzzy clustering with Maximum count. In this process choose the pattern as centroid which clusters the maximum number of patterns of its own class using fuzzy membership function [22]. After completing the clustering process, perform Pruning algorithm for reducing the single pattern clusters. The fuzzy membership function is given by

$$f(l, r_j) = \begin{cases} 1 & l \le r_j \\ r_j/l & \text{otherwise} \end{cases}$$

where l is a euclidean distance between the input pattern and centroid of j th FSH, while rj is the radius of FSH. b) The output layer is constructed by creating the class nodes connected with the associated FSHs from the hidden layer, that are created during clustering for that class. However, the accuracy of these systems is compromised as the system mostly works on inaccurate data and inputs. To overcome this problem, this research work introduced an enhanced lion optimization algorithm (ELOA).

Enhanced Lion Optimization algorithm

Traditional SLnO The traditional SLnO algorithm was developed with the raw motivation acquired from the hunting behavior of Sea lions [26]. The sea lion are gifted with certain fasctianting features like speedy movement, improved hunting property and lucid vision. Further, Whiskers is the super sensitive feature of sea lion that helps in tracking as well as searching the prey. Moerover, these whiskers also aids in defning the position, shape, and size of prey. The major phases of the hunting behavior of sea lions are depcited below:

• Prey tracking as well as chasing with the aid of their whiskers.

• Following the prey and encircling it by means of calling other sea lions that belong to its subgroup.

• Prey attacking

Mathematical model: there are four major phases in the SLnO algorithm, they are tracking, social hierarchy, attacking and encircling prey.

Phase 1—Prey detection and tracking: the whiskers of sea lion help them to sense the existing prey and determine their position, while the direction of whiskers is opposite to the direction of the water waves. They have the ability of identifying the location of the prey and then call the members in its sub-group to join along with it to chase and hunt the prey. For this mechanism of hunting this sea lion which calls others are said to be the leader and the others update their position with correspondence to the target prey. Here, the target prey is assumed to be the current best solution or close to optimal solution. This behaviour is mathematically explained as per Eq. (10). Here, Di $^{\rightarrow}$ indicates the distance between the target prey and the sea lion. In addition, the notation M(t) and L (t) indicates the vector position of sea lion and target prey, respectively. The current iteration and the random vector in the interval [0, 1] is denoted using the symbol t and J$^{\rightarrow}$, respectively. Next to the current iteration, the sea lion moves to a position over the target prey to get much closer to the prey. The mathematical expression for this behavior of sea lion in the subsequent iteration is expressed in Eq. (11). The next iteration is symbolized as (t + 1) and over the course of iterations, the value of H$^{\rightarrow}$ gradually lessens from 2 to 0.

$$\overrightarrow{Di} = \left|2\vec{J}.\overrightarrow{M}(t) - \overrightarrow{L}(t)\right|$$

$$\vec{S}(t+1) = \overrightarrow{M}(t) - \overrightarrow{Di}.\vec{H}$$

Phase 2—Vocalization: the sea lions have the ability of surviving both in land and in water (amphibians). In water, the sound of the sea lion is four times quicker, while compared to their sound in air. Further, numerous vocalization is being utilized by sea lions to communicate with others during chasing or hunting process. They also use their sound to call other members to stay on the shore. The sea lions have smaller ears to detect sounds both under and above water. Thus, when a sea lion tends to identify a prey, it calls the other members to join it for encircling and attacking the prey. The mathematical expression for this behaviour of sea lion is expressed in Eqs. (12), (13) and (14), respectively. The speed of sea lion is symbolized as LP→ leader and the speed of their sound in water and air is indicated as R→1 and R→2.

$$\overrightarrow{LP_{leader}} = \left|\left(\overrightarrow{R_1}(1+\overrightarrow{R_2})\right)/\overrightarrow{R_2}\right|$$

$$\overrightarrow{R_1} = \sin\theta$$

$$\overrightarrow{R_2} = \sin\varphi$$

Phase 3—Attacking phase: Here, in the exploration phase, the sea lions get the ability of recognizing the location of the target prey as well as encircling them. The best search agent said to be the leader guide the hunting mechanism. The current candidate best solution is nothing but the target prey. In this phase, two major sub- phases like Dwindling encircling technique and Circle updating position are present. Dwindling encircling approach: In Eq. (12), this encircling mechanism takes place in correspondence to H→ value. Further, over the course of iterations, the value of H→ is lessened from 2 to 0. This lessening of H→ value aids the sea lion leader to move towards the prey and encircle them. Thus, the position of the incoming sea lion can be localized at any position in the search space in between the search agents premier location and present best agent.

Circle updating position: bait ball of fshes are searched by the sea lion and then start hunting from the edges. On the basis of this searching and hunting mechanism, Eq. (15) is defned. The distance in between the best optimal solution (target prey) and the search agent (sea lion) is symbolized as | | | M→(t) − L→(t) | | | . In addition, the absolute value and the random number in [-1, 1] is represented as | | and l, respectively.

$$\vec{L}(t+1) = \left|\overrightarrow{M}(t) - \vec{L}(t).\cos(2\pi l)\right| + \overrightarrow{M}(t)$$

Phase 4—Prey searching: with the help of the whiskers, the sea lions randomly search and swimming zigzagging to find prey. On the basis of the best search agent, the sea lions tend to update their position in the exploitation phase. On the other hand, with correspondence to the randomly selected sea lion, the position of the search agent is updated in the exploration phase. The global search in SLnO algorithm accomplished when the value of H→ is larger than 1.

This process is expressed mathematically in Eqs. (16) and (17), respectively.

$$\overrightarrow{Di} = \left|2\vec{J}.\overrightarrow{L_{rnd}}(t) - \vec{L}(t)\right|$$

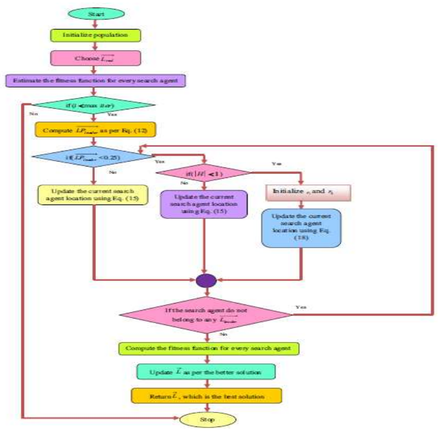
$$\vec{L}(t+1) = \overrightarrow{L_{rnd}}(t) - \overrightarrow{Di}.\vec{H}$$

4.4 Proposed algorithm

The traditional SLnO algorithm still requires improvement in position update at the exploration phase and so a novel algorithm called Sea Lion with Enhanced Exploration phase (SLnO-EE) is developed here. The steps involved in the proposed SLnO-EE model are described below: Initially, two random numbers r1 and r2 are initialized. Generally, in the exploration phase (i.e., attacking phase), the traditional SLnO updates the position of the current search agent using the mathematical expression depicted in Eq. (17). As a controversy to this, the proposed SLnOEE algorithm updates the position of the current search agent using Eq. (18).

$$\overline{S}(t_1\ :) = x(t_1\ :) + r_1 * \left(best - abs\left(x(t_1\ :)\right) - \right.$$
$$\left. -r_2 * \left(worst - abs\left(x(t_1\ :)\right)\right)\right) \tag{18}$$

Where, r1 and r2 are the two random numbers. The best and the worst solution are indicated as best and worst, respectively. The pseudo-code of the proposed SLnO-EE model is shown in Algorithm 1. The fow chart of the proposed SLnO-EE is exhibited in Fig. 4.



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