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Tuna Swarm Algorithm Based Robust Node Localization Scheme in Wireless Communication Networks

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Abstract

Node Localization (NL) in wireless sensor networks (WSNs) is main procedure for defining physical matches such as longitude, latitude, and altitude of Sensor Nodes (SNs) organized in a provided region. Exact NL is very essential for numerous WSN applications like surveillance, asset tracking and environmental monitoring. Localization models involve GPS hardware, anchor nodes with recognized locations or algorithms that influence distance dimensions and connectivity designs amongst SN in order to evaluate their places. Trustworthy NL improves exactness and efficiency of data collection and study in WSNs, finally boosting up the network's performance and quality information it offers. This article introduces a tuna swarm algorithm-based node localization (TSA-RNL) technique in WSN. The major aim of the TSA-RNL model to focus unknown nodes in WSN. TSA-RNL technique is developed for enhancing the localization accuracy in the WSN. The TSA, stimulated from the collective nature of tuna fish, optimizes the localization process by iteratively refining node positions. Over wide simulation and experimentation, we estimate the TSA-RNL model performance and establish its authority in gaining great accurateness node localization in WSNs. The methods provide potential advantages for many applications that based on specific node positioning, environmental monitoring, data fusion and target tracking that contributing to the development of WSN methodology.

Keywords: Node Localization, Sensor Node (SN), Target Node, Tuna Swarm Algorithm (TSA), Wireless Sensor Network.

Introduction

WSN is common type of networks of distributed autonomous nodes which can wisdom their atmosphere supportively (1). WSNs are mainly employed in different applications like healthcare, traffic surveillance, home automation, environment and habitat monitoring and structural health monitoring (2). WSN nodes observe their environment via on-board sensors in monitoring applications. Location is very vital in WSNs because it is employed for monitoring as well as tracking applications (3). In addition, the Location data is utilized to identify and record actions, or to route packets by employing geometric-aware routing. Preparing every node with a worldwide positioning network is not a best solution due to size, cost and energy limitations (4). Node localization denotes to generating location consciousness in entire organized SNs so it become an area of active study. The sensor sites are frequently unidentified due to the deployment of arbitrary node. As an outcome, defining the physical places of the SNs is a very essential problem in WSNs (5). The main aim of WSN localization is to define the SNs positions in a network specified imperfect and noisy pairwise time-of-arrival (TOA), angle-of-arrival measurements, customary signal strength and time-difference-of-arrival that are needed by the devices at the time of communications with their neighbors.

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A typical assumption is the sites of some nodes which is known as anchors accurately, so it is highly probable to find out the complete places of the remaining nodes in WSN (6). The two chief aims that must be measured while planning a protocol of localization for sensor networks are scalability and accuracy (7). Several localization models in the literature have mainly focused on employing a quantity of specialized nodes in their places. Such specialized nodes are generally termed as anchors nodes (8). Whereas the remaining nodes effort to estimate their place by replacing data to together decide their distances to the anchors. Many anchor-based models need a high-level percentage of anchor nodes to reach a satisfactory exactness (9). Also, the addition of a GPS receiver on every node is not useful due to the energy consumption, form factor and cost, enlarged sensor difficulty and also the sensitivity of GPS receivers to link of sight situations. However, many models undergo from scalability issue (10).

This article introduces a Tuna Swarm Algorithm-Based Node Localization (TSA-RNL) technique in WSN. One of the major goals of TSA-RNL method to localize unknown nodes in WSN. The TSA-RNL technique is developed for enhancing the localization accuracy in the WSN. The TSA, stimulated from the collective nature of tuna fish, optimizes the localization process by iteratively refining node positions. By using wide simulation and experimentation, the research estimate the TSA-RNL models performance and establish its authority in attaining extremely precise node localization in WSNs.

A New High-Precision and High-Robustness Localization (NHHL) technique was developed, in which a unique non-convex localization problem was first transformed into an alternating non-negative constrained least squares (ANCLS) architecture. Additionally, a consequence function was employed. Subsequently, the localization problem was further reformulated into a Generalized Trust Region Sub-Problem (GTRS), and an interior-point model was used for the initial estimation. Finally, the solution was iteratively obtained using a block coordinate descent approach to determine both the position and the path loss factor (PLF) jointly (11). A study was presented that aimed to enhance the standard DV-Hop method, where an improved cosine similarity parameter was introduced. Furthermore, a hybrid model combining modified particle swarm optimization (PSO) with simulated annealing was employed to refine the initial position estimates of unknown nodes, which were derived using a trilateration approach within the modified DV-Hop framework (12).

A Robustness Enhanced Sensor-Assisted Monte Carlo Localization (RESA-MCL) model was proposed. This approach demonstrated improved localization accuracy and robustness against malicious threats or faulty nodes. To evaluate the model's resilience, three types of attack strategies based on malicious anchor nodes were simulated and compared with existing techniques (13). A novel model combining Kalman Filtering (KF) with a Radial Basis Function Neural Network (RBFN), referred to as RBFN+KF, was introduced. The model's performance was assessed using simulated Received Signal Strength Indicator (RSSI) data and was benchmarked against Multilayer Perceptron (MLP), trilateration, and conventional RBFN-based localization techniques (14).

An anchor node selection scheme was proposed for RSS-based localization in WSNs. The method involved an initial arrangement of nodes to enable rational anchor selection, and weights were assigned to each anchor node to mitigate the effect of selection errors. An enhanced cuckoo search algorithm was then employed to estimate the positions of unknown nodes (15). A framework was developed for threat detection and localization in IoT-enabled WSNs. This approach integrated trust estimation with blockchain-based cascade encryption in a hierarchical architecture. Federated machine learning (FML) was incorporated to ensure data security and communication integrity by aggregating device-level data and identifying malicious activity on the blockchain. Harmful nodes were classified using a combination of support vector machines (SVM), ensemble learning, gradient boosting, hybrid random forest (RF), and k-means clustering, following a feature evaluation process (16).

Methodology

In this research paper, a novel development of TSA-RNL approach in WSN is proposed. The major aim of the TSA-RNL method is to focus the unfamiliar nodes in WSN. The TSA-RNL technique is developed for enhancing the localization accuracy in the WSN. Figure 1 defines the overall process of TSA-RNL system.

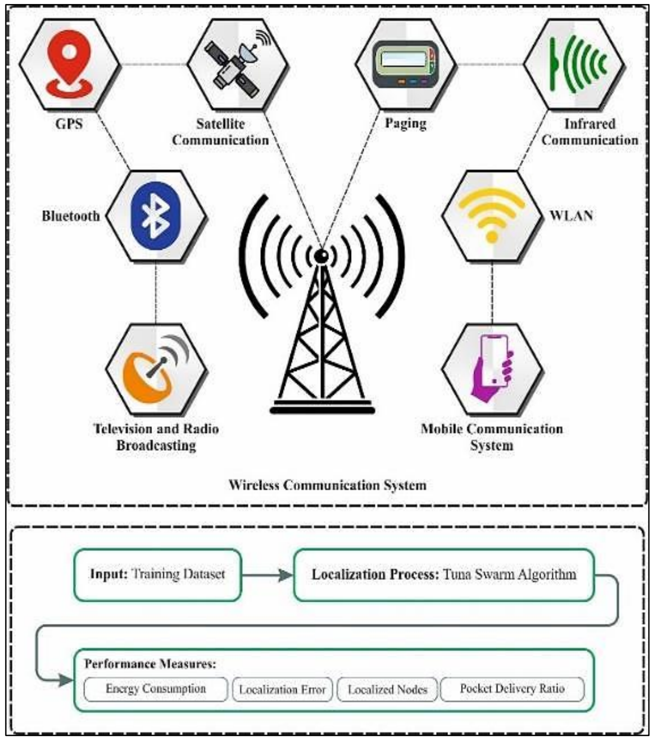

Figure 1: Overall Procedure of TSA-RNL Model

To balance localization accuracy and computing performance, algorithm parameters were carefully selected and optimized in the TSA-RNL framework. The population size was 30, which balanced convergence quality and execution time based on empirical tweaking and published benchmarks. The maximum iteration was 100, which was adequate for steady localization accuracy without significant processing expense. Adopting adaptive weight settings ($W\ u\ a\ x$ = 0.9 W max=0.9 and $W\ u\ i\ n$ = 0.4 W min=0.4) improves the exploration-exploitation balance of the method. These parameters were set to retain variety early in optimization and speed convergence later. The chosen parameters have a practical and theoretically good calibration for WSN node localization. TSA model starts the optimization procedure by uniformly and randomly creating initial populace in the search collection (17). The TSA can be exactly expressed as below:

$$X_1^{int} = rand \cdot (ub - lb) + lb, i = 1,2, \dots, NP \qquad [1]$$

In Equation [1], X_i^{int} signifies the original place of i-th individual, lb and Ub is the lower and upper limits of search spaces similarly. NP denotes tuna population quantity. Normally, this weighted value marks optimal rate of TSA and then equally dispersed random vector. Spiral foraging (SF) is one of the main techniques of tuna schools that races target through creating fitted spirals. Beside with racing target, tuna schools transform information by all others. Each tuna is ordered as well as sturdily connected; so adjacent tuna share information. The SF method arithmetically calculated as follows:

$$X_1^{t+1} = \{\alpha_1 \bullet (X_{best}^t + \beta \bullet |X_{best}^t - X_i^t|) + \alpha_2 \bullet X_i^t, i = 1, \alpha_1 \bullet (X_{best}^t + \beta \bullet |X_{best}^t - X_i^t|) + \alpha_2 \bullet X_{t-1}^i, i = 2,3, \dots, NP, \qquad [2]$$

$$\alpha_1 = \partial + (1 - a) \bullet \frac{t}{t_{max}}, \qquad [3]$$

$$\alpha_2 = (1-a) - (1-a) \bullet \frac{T}{t_{max}}, \quad [4]$$
$$\beta = e^{bl} \bullet cos\ (2\pi b), \quad [5]$$
$$l = e^{3\ cos\ (t_{max}+1/t)-1)\pi)}, \quad [6]$$

Where $best$ signifies the present better individual (food), X_i^{t+1} represents i-th individual of $t+1$ iteration, a shows endless that outlines that range tuna follows improved and prior individual at first stage, t and t_{max} specifies the current and the high amount of iterations, $\alpha_1$and α_2 indicates the weight constant that manages the action trends of individual to the improved as well as earlier individuals, and b is evenly distributed random number between [0, 1]. Once the optimal person not capable to locate food, sightlessly subsequent finest individual foraging is not beneficial to the cluster foraging. Therefore, for helping each person in consuming finest spatial hunt capabilities, a reference point for spiral search must be provided to generate a casual manage in the hunt system, so permitting TSA to have greatest global exploration aptitudes, and it will provide accurate expression by Equation [7]:

$$X_1^{t+1'} = \{\alpha_1 \bullet (X_{rand}^t + \beta \bullet |X_{rand}^t - X_i^t|) + \alpha_2 \bullet X_i^t, i = 1, \alpha_1 \bullet (X_{rand}^t + \beta \bullet |X_{rand}^t - X_i^t|) + \alpha_2 \bullet X_{i-1}^t, i = 2,3, \dots, NP, \quad [7]$$

Whereas in the search ranges, the X_{rand}^t signifies random reference point, TSA are classically discovered extensively worldwide at an initial phase and next gradually transitioned to precise local exploitation by growing sum of iterations. TSA leisurely modifies the SF reference point from arbitrary person to optimal individual at the beginning. The SF method can be calculated by Equation [8]:

$$X_1^{t+1'} = \{\{\alpha_1 \bullet (X_{best}^t + \beta \bullet |X_{best}^t - X_i^t|) + \alpha_2 \bullet X_i^t, i = 1, \alpha_1 \bullet (X_{best}^t + \beta \bullet |X_{best}^t - X_i^t|) + \alpha_2 \bullet X_{i-1}^t, i = 2,3, \dots, NP, \quad if rand \geq \frac{t}{t_{max}} \{\alpha_1 \bullet (X_{rand}^t + \beta \bullet |X_{rand}^t - X_i^t|) + \alpha_2 \bullet X_i^t, i = 1, \alpha_1 \bullet (X_{rand}^t + \beta \bullet |X_{rand}^t - X_i^t|) + \alpha_2 \bullet X_{i-1}^t, i = 2,3, \dots, NP, \quad if rand < \frac{t}{t_{max}} \quad [8]$$

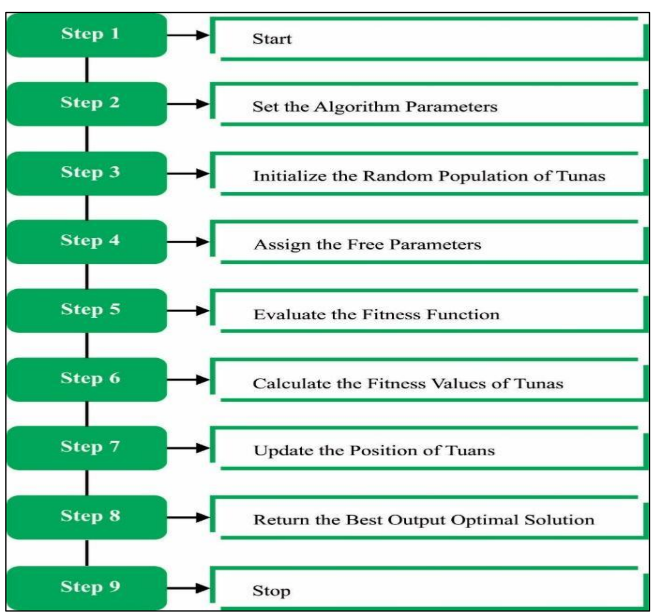

Figure 2: Steps Involved in TSA

Tuna selects SF with parabolic cooperative foraging. Tuna creates a parabola with directed food to Z-point as a reference. Tuna discoveries the beset food by hunting around the parabola. Both tuna foraging techniques are executed depend upon the possibility portion, and if the assortment possibility for dual foraging models is ½. At last, they are simultaneously executed, and it can be exactly expressed as follows.

$$X_1^{t+1} = \{X_{best}^t + rand \bullet (X_{best}^t - X_1^t) + TF \bullet p^2 \bullet (X_{best}^t - X_i^t), ifrand < 0.5, TF \bullet p^2 \bullet X_1^t, ifrsnd \geq 0.5, \quad [9]$$

$$p = \left(1 - \frac{t}{t_{max}}\right)^{(t/t_{max})}, \quad [10]$$

Whereas TF indicates random integer within $[1, -1]$. Figure 2 depicts the steps involved in TSA. The TSA-RNL localization method mainly used to define the organize points of sensors. Main objective of localization node in WSN is to calculate the organized facts of preferred node by diminishing the impartial work. In WSN, the localization issue is measured optimization problem established employing many metaheuristic techniques. The developed method was employed in order to discover the sensor in WSN. Locate M and N as target ACN in a random method in sensor area. Whole ACN are prepared through place attention for identifying the place. Entire anchor and TNs include transmission range$R$. Space among the ACN and target are evaluated and adapted utilizing improver Gaussian noise. The TN signifies space by $\hat{d}_i = d_i + n_i$ whereas d_i indicates real distance that was calculated among place of TNs (x, y) then position of beacon (x_i, y_i) employing the provided task:

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad [11]$$

The variable n_i defines noise which marks calculated distance from $d_i \pm d_i \left(\frac{P_n}{100}\right)$ while P_n indicates noise ratio in valued distance. The required node is known a localizable node once it encloses 3 ACN in the communication range of TN. Afterwards, the basis depends upon trilateral locating unit, organize three ACN (x_1, y_1), $B(x_2, y_2)$, and $C(x_3, y_3)$, and the space among TN d_i and 3 ACN are recognized. Then, the usage of trigonometric rules of cosine/sine, the TN coordinate is definite. Similarly, in multi alteration TN valued unit, space metrics of enormous ACN used for reducing the fault from a unique and assessed distance.

The TSA-RNL model is separately executed in order to recognize the location of the TN in occurrence of localizable node. The coyotes are required by centre ACN inside transmission range by provided task:

$$(x_c, y_c) = \left(\frac{1}{N}\sum_{i=1}^{N} x_i, \frac{1}{N}\sum_{i=1}^{N} y_i\right) \quad [12]$$

The N represents sum of ACN in the transmission choice of localizable TN.

TSA-RNL technique is highly suitable for classifying the coordinates (x, y) of TN, which reduces localization error (LE). The primitives engaged in localization issue is a mean square distance among mark and ACN that is diminished by given model:

$$f(x, y) = \frac{1}{N}\left(\sum_{i=1}^{N} \sqrt{(x - x_i)^2 + (y - y_i)^2} - \hat{d}\right)^2 \quad [13]$$

While $N \geq 3$ symbolizes sum of ACN in a transmission radius of TN.

The optimal quantity (x, y) was defined through TSA-RNL element when total of rounds is controlled. The sum LEs are determined when estimating localizable TNsN_L. This is calculated as a mean square of space from distinct node coordinates (X_i, Y_i) whereas the actual node coordinates (x_i, y_i) are provided by:

$$E_1 = \frac{1}{N_1}\sum_{i=1}^{N} \sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2} \qquad [14]$$

The two to six process is sustained till the TN is restricted. The localization node depends upon greatest LE E_1 as well as quantity of unlocalized nodes N_{N_L} are determined in use of $N_{N_L} = M - N_L$. Least scores of E_1 and N_{N_L} enhances an actual localization.

The node localization quantity obtains improved when the repetition boost. Similarly, it decreases the anchor node sum within transmission range of the localizable TN, and valued place of TN performance as an anchor node in the succeeding iteration. It is mainly employed in order to limit the issue of flip hesitation that produces greatest LE. Once the repetition is boosted, the process period to localization data of TN enhances.

Results and Discussion

In this section, the investigational validation of the TSA-RNL technique is examined. Table 1 and Figure 3 represents a comparative localized nodes (LN) results of the TSA-RNL technique under varying ANs. The experimental values highlighted that the TSA-RNL technique obtains maximal LN values. With 10 ANs, the TSA-RNL technique gains increased LN of 141 whereas the COA, BOA, GSA, CSO, and KHA models obtain decreased LN values of 134, 123, 119, 111, and 109 respectively.

Table 1: LN Outcome of TSA-RNL Approach with Other Methods under Various Anchors

Localized Nodes						
Anchor Numbers	**TSA-RNL**	**COA-Protocol**	**BOA-Protocol**	**GSA-Protocol**	**CSO-Protocol**	**KHA-Protocol**
10	141	134	123	119	111	109
20	156	149	132	128	124	111
30	178	170	149	145	126	120
40	179	172	158	150	141	128
50	199	193	172	163	149	139

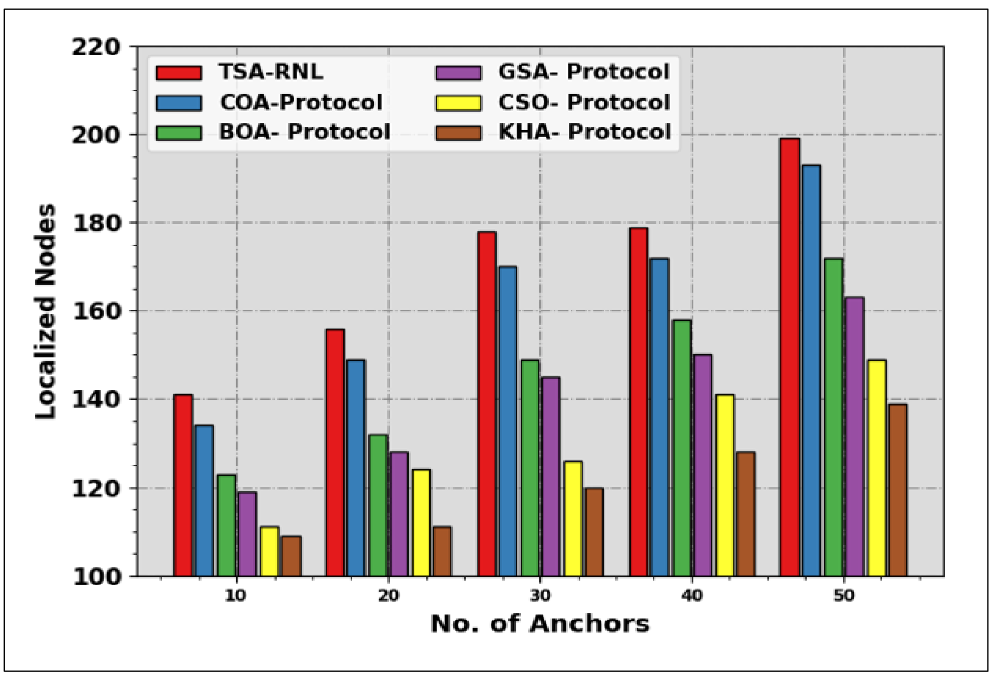

Figure 3: LN Outcome of TSA-RNL Approach under Various Anchors

Meanwhile, based on 20 ANs, the TSA-RNL method attains raised LN of 156 while the COA, BOA, GSA, CSO, and KHA methods get reduced LN values of 149, 132, 128, 124, and 111 individually. Also, on 30 ANs, the TSA-RNL method attains raised LN of 178 but, the COA, BOA, GSA, CSO, and KHA methods acquire diminished LN values of 170, 149, 145, 126, and 120 correspondingly.

The localization error (LE) results of the TSA-RNL technique are compared with existing models under changing ANs, in Table 2 and Figure 4. The results indicate that the KHA and CSO models have reported maximum LE values whereas the BOA and GSA models accomplish slightly decreased LE values. Meanwhile, the COA model has managed to report considerable LE values. But the TSA-RNL technique shows better performance with minimal LE of 0.18, 0.15, 0.13, 0.03, and 0.05, under ANs of 10-50 respectively (Table 2).

Table 2: LE Outcome of TSA-RNL Approach with Other Methods under Various Anchors

Localization Error						
Anchor Numbers	**TSA-RNL**	**COA-Protocol**	**BOA-Protocol**	**GSA-Protocol**	**CSO-Protocol**	**KHA-Protocol**
10	0.18	0.33	0.44	0.54	0.69	0.67
20	0.15	0.31	0.39	0.49	0.64	0.69
30	0.13	0.25	0.35	0.47	0.50	0.54
40	0.03	0.17	0.33	0.41	0.48	0.50
50	0.05	0.16	0.27	0.37	0.45	0.47

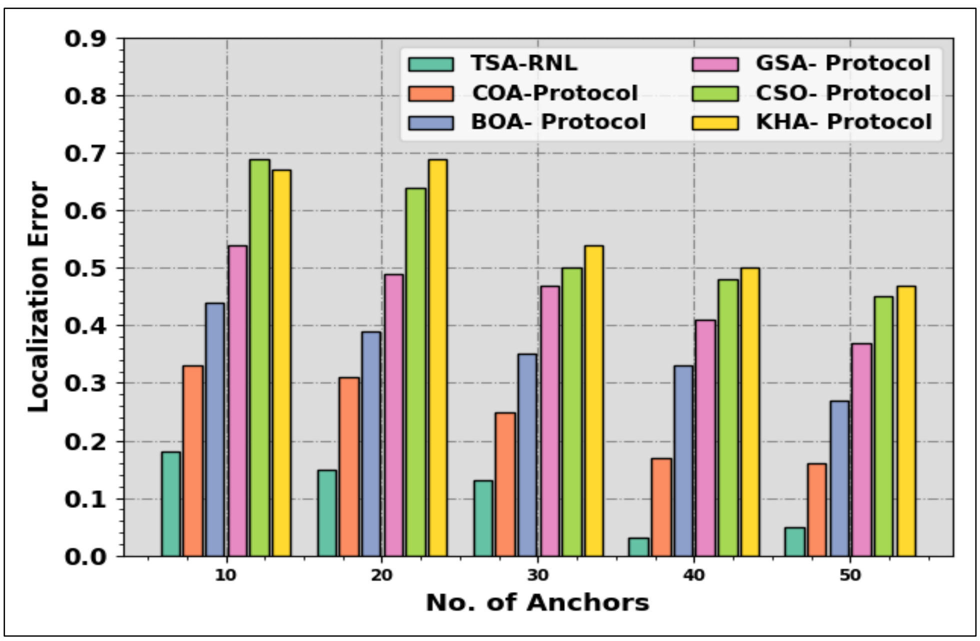

Figure 4: LE Outcome of TSA-RNL Approach under Various Anchors

Table 3 depicts the LE outcome of TSA-RNL approach with other methods under various range error (RE) and transmission range (TR). The LE results of the TSA-RNL approach are compared with existing models with changing RE, in Figure 5. The outcome value specifies that the KHA and CSO methods are stated higher LE values while the BOA and GSA models get moderately reduced LE values. Additionally, the COA technique is managed to show remarkable LE values. However, the TSA-RNL approach exhibit higher performance with reduced RE of 0.24%, 0.15%, 0.09%, 0.10%, and 0.09%, with REs of 10%-30% ranges correspondingly.

Table 3: LE Output of TSA-RNL Approach with Other Methods

Localization Error						
Range Error (%)	**TSA-RNL**	**COA-Protocol**	**BOA-Protocol**	**GSA-Protocol**	**CSO-Protocol**	**KHA-Protocol**
10	0.24	0.28	0.37	0.44	0.62	0.63
15	0.15	0.22	0.36	0.39	0.55	0.63
20	0.09	0.16	0.34	0.38	0.50	0.54
25	0.10	0.13	0.33	0.36	0.44	0.49
30	0.09	0.12	0.29	0.30	0.42	0.45
Transmission Range (m)	**TSA-RNL**	**COA-Protocol**	**BOA-Protocol**	**GSA-Protocol**	**CSO-Protocol**	**KHA-Protocol**
10	0.14	0.19	0.34	0.34	0.49	0.54
15	0.11	0.16	0.23	0.31	0.45	0.48
20	0.09	0.15	0.21	0.31	0.46	0.51
25	0.05	0.10	0.12	0.25	0.36	0.40
30	0.03	0.08	0.12	0.22	0.35	0.42

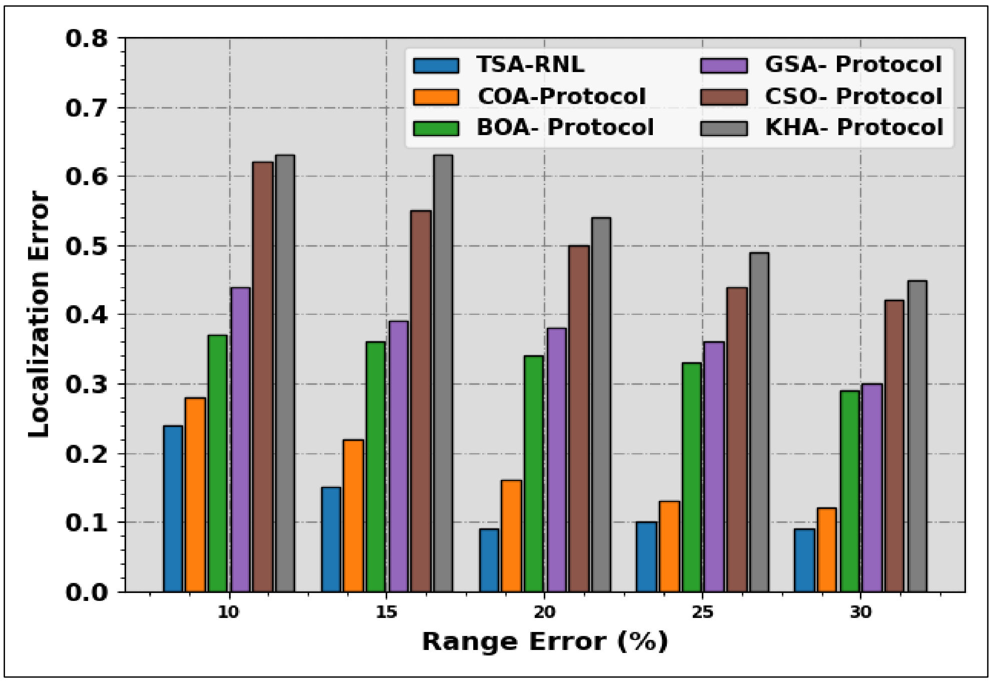

Figure 5: LE Outcome of TSA-RNL Approach under Various Range Errors

The LE analysis of the TSA-RNL technique can be compared with existing approaches with modifying TR, in Figure 6. The outcome value shows that the KHA and CSO models are specified better LE values but, the BOA and GSA models get moderately reduced LE values. Moreover, the COA approach is managed to show significant LE values. Then, the TSA-RNL approach reveal greater performance with reduced LE of 0.14%, 0.11%, 0.09%, 0.05%, and 0.03%, with TRs of 10m-30m ranges respectively.

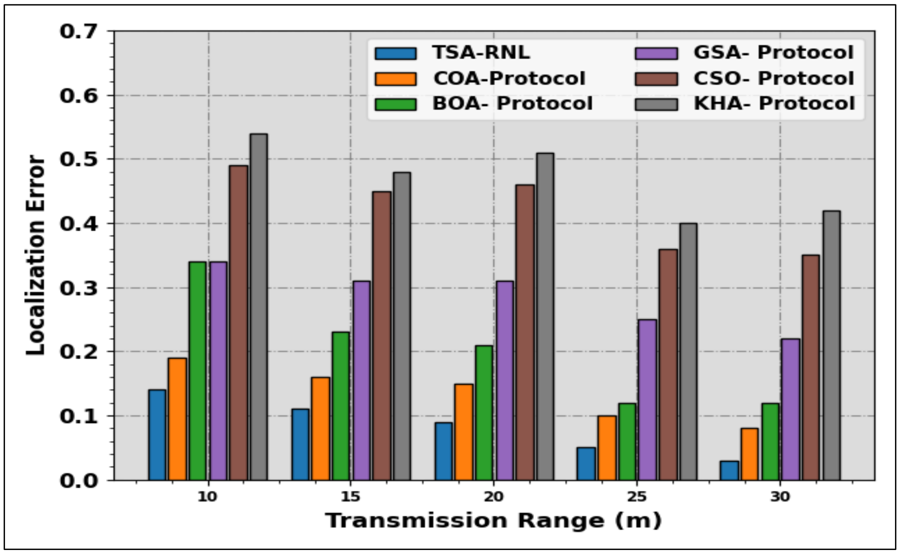

Figure 6: LE Outcome of TSA-RNL Approach under Various Transmission Range

Table 4 demonstrates the comparative outcome of TSA-RNL system with recent approaches in terms of energy consumption (ECOM) and packet delivery ratio (PDR). The ECOM analysis of the TSA-RNL system is compared with recent techniques with changing nodes, in Figure 7. The outcome value specifies that the KHA and CSO models are provided maximum ECOM values whereas the BOA and GSA models get slightly reduced nodes values. Then, the COA model has accomplished to show considerable ECOM values. However, the TSA-RNL model exhibits excellent performance with decreased ECOM of 54mJ, 90mJ, 109mJ, 122mJ, and 160mJ, under nodes of 200-1000 correspondingly.

Table 4: ECOM and PDR Outcome of TSA-RNL Approach with Other Methods under Various Nodes

No. of Nodes	KHA-Protocol	CSO-Protocol	GSA-Protocol	BOA-Protocol	COA-Protocol	TSA-RNL
Energy Consumption (mJ)						
200	179	170	99	87	66	54
400	207	199	137	114	99	90
600	230	217	177	142	121	109
800	275	250	190	172	132	122
1000	311	289	216	197	168	160
Packet Delivery Ratio (%)						
200	95.37	97.69	98.59	99.47	99.89	99.95
400	93.68	96.58	97.61	98.49	99.43	99.74
600	91.59	94.50	95.52	97.57	98.26	98.97
800	89.63	92.41	94.61	96.46	97.41	98.40
1000	87.28	90.77	93.63	95.48	96.36	97.69

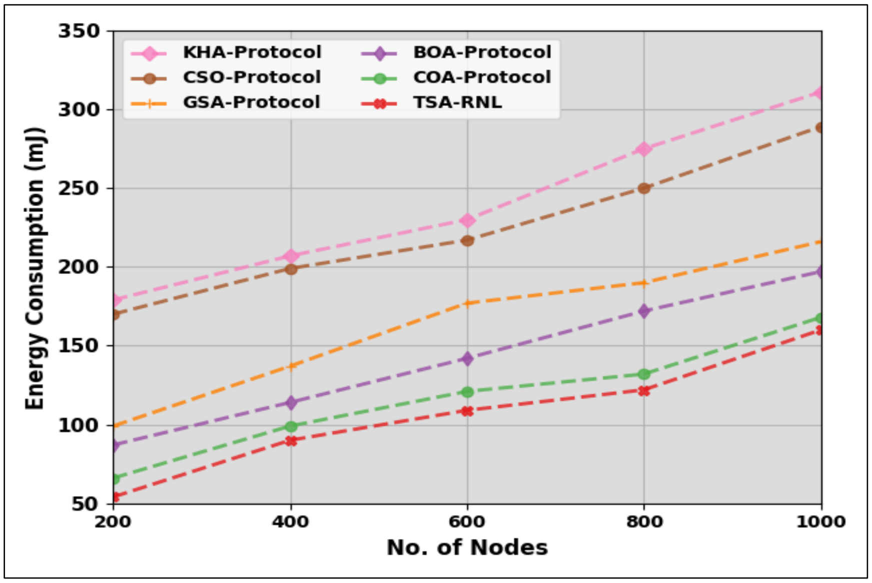

Figure 7: ECOM Outcome of TSA-RNL Approach under Various Nodes

The PDR analysis of the TSA-RNL methodology is compared with existing systems under changing nodes, in Figure 8. The outcome value that the KHA and CSO models are reported greater LN values while the BOA and GSA models obtain slightly diminished PDR values. Also, the COA technique has accomplished to report remarkable PDR values. But the TSA-RNL technique exhibits exceptional performance with minimal PDR of 99.95%, 99.74%, 98.97%, 98.40%, and 97.69%, under nodes of 200-1000 respectively.

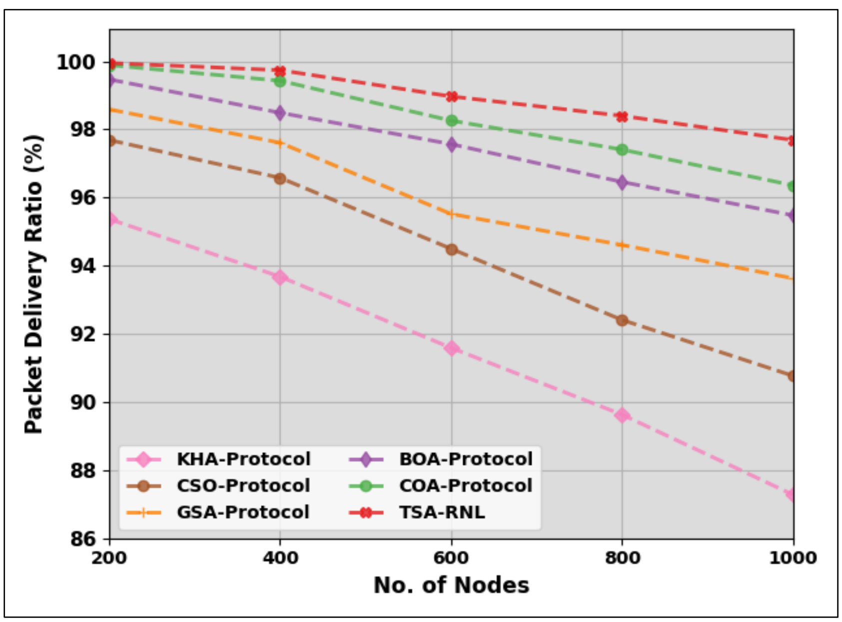

Figure 8: PDR Outcome of TSA-RNL Approach under Various Nodes

Conclusion

In this article, a new introduces a TSA-RNL technique in WSN. The main aim of the TSA-RNL model is to find out the unknown nodes in WSN. TSA-RNL technique is developed for enhancing the localization accuracy in the WSN. The TSA, stimulated from the collective nature of tuna fish, optimizes the localization process by iteratively refining node positions. With help of wide simulation and experimentation, we estimate the TSA-RNL approach performance and establish its authority in reaching great exactness node localization in WSNs. The method comes with many highly benefits for applications that trust on exact node positioning with target tracking, environmental monitoring, data fusion and contributing to the improvement of WSN machinery. The key restriction found is TSA-RNL's centralized character, which could influence real-time scalability in very dynamic surroundings. To improve flexibility and robustness even further, we want to investigate distributed implementations, lightweight hybrid models, and machine learning-enhanced localization methodologies in next work.

Abbreviations

GTRS: Generalized Trust Region Sub-Problem, MCL: Monte Carlo Localization, NL: Node Localization, PSO: Particle Swarm Optimization, RNL: Robust Node Localization, RSSI: Received Signal Strength Indicator, SN: Sensor Node, TSA: Tuna Swarm Algorithm, WSN: Wireless Sensor Network.

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Author Contributions

JK Periasamy: Conceptualization, Data Curation, Writing—original draft preparation, review, editing, Project administration, Shrabani Mallick: Methodology, Sridevi Chitti: Software, Writing—review editing, S Sivasakthi: Validation, Investigation, Writing—review, editing, Visualization, Bindu K V: Formal analysis, Resources, supervision, Ezudheen Puliyanjalil: Validation, Writing—review, editing.

Conflict of Interest

The authors have expressed no conflict of interest.

Ethics Approval

Not applicable. This study does not involve any human participants or animal subjects.

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