Modeling of chimp optimization algorithm node localization scheme in wireless sensor networks

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ABSTRACT

For smart environments in the digital age, wireless sensor networks (WSNs) are needed. Node localization (NL) in WSNs is complicated for recent researchers. WSN localization focuses on finding sensor nodes (SNs) in two dimensions. WSN NL provides decision-making information in packets sent to base stations. This article describes modeling of chimp optimization algorithm node localization system in wireless sensor networks (MCOANL-WSN). The MCOANL-WSN approach uses metaheuristic optimization to locate unknown network nodes. To simulate chimpanzees' cooperative hunting behavior, the MCOANL-WSN approach includes chimp optimization algorithm (COA) into the NL process. The system uses mathematical modeling to represent node collaboration to improve placements. COA-based localization is being proposed for dynamically responding to resource-constrained and dynamic WSNs. Wide-ranging simulations may assess the MCOANL-WSN system's scalability, energy efficiency, and localization accuracy. The findings demonstrate the superiority of the new modeling method over current NL schemes in improving WSN reliability and efficiency in various applications.

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1. INTRODUCTION

Wireless sensor networks (WSNs) comprise several millions of nodes. WSN based system has been effectively used in applications including smart structure, industrial or home automation, and environmental monitoring [1]. The data generated by the single node or entity is of limited usage without knowing its position in internet of things (IoT) and WSN applications. The location information is required to report geographically significant data [2]. Also, it is needed for services like disaster event notifications, coverage area management, context-based, location-aware services, routing and geographic protocols [3]. The WSN features include rapid deployment and self-organization making it potential for the WSN applications. In the

WSN application, sensor node (SN) senses and reports the event of interest that is inspected once the target node position reports the event is identified. The estimation of SN is the critical issue of WSN and is called as localization problems [4]. The technology of node localization (NL) could track and locate nodes, such that the monitoring information are m more substantive, viz., information collected at sink nodes would be worthless to the user without NL data in the sensor field [5]. The NL is defined as position determination the of the unknown SNs known as target nodes using the known location of the SNs termed as anchor node according to the quantities like arrival time, time variance of arrival, triangulation and maximal likelihood arrival angle, and so on [6]. The NL issue of WSN should be solved by applying global positioning system (GPS) with SNs, but it is not favoured owing to its size, energy and cost problems. Hence, superior and effectual alternative is required for localizing the SNs [7]. The non-GPS-based localization system is classified into range-free and range-based models.

In recent times, NL in WSN can be managed as a multidimensional, and multimodal optimization problems are overcome by population-based stochastic algorithms [8]. In this work, several metaheuristic approaches are utilized to resolve the NL issues in WSN. This method was succeeded in dramatically declining the localization errors. It attempts to resolve an optimization issue using trial and error where the feasible solution is processed, and the nearby the finest solution is detected [9]. Presently, different optimization techniques such as particle swarm optimization (PSO), cuckoo search (CS), genetic algorithm (GA), butterfly optimization algorithm (BOA), gravitational search algorithm (GSA), and artificial bee colony (ABC), which are effectively applied to specify the position of unknown node in WSN [10].

This article offers the modeling of chimp optimization algorithm node localization system in WSNs (MCOANL-WSN) technique. The MCOANL-WSN method implements a modeling architecture that incorporates the distinctive features of chimp optimization algorithm (COA), recognized for its stimulation from the cooperative hunting behavior of chimpanzees, into the NL procedure. The system is applied mathematical modeling for signifying the collaborative schemes of nodes in enhancing their locations. Additionally, the COA-based localization model is considered for adapting dynamically to the resource-constrained and dynamic type of WSNs. The performance of the MCOANL-WSN system can be measured via wide-ranging simulations, considering crucial metrics like scalability, energy efficiency, and localization accuracy.

2. LITERATURE SURVEY

Zhang *et al*. [11] goal is to improve the node utilization of underwater WSN utilizing intelligent optimizer systems and robot collaboration tool. The research uses the chemical reaction optimizer (CRO) model that incorporates the profits of inherited methods, simulation annealing method, and Ant colony algorithm (ACA). The CRO model is improved over an architecture alteration role. Moreover, the autonomy and flexibility of robots are leveraged. Zhang *et al*. [12] developed the hybrid system shuffled frog leaping algorithm (SFLA)-WOA (SWOA) dependent upon the whale optimization algorithm (WOA) and SFLA. The SWOA process integrates the benefits of WOA and SFLA; it recollects the exclusive evolution technique of WOA and the outstanding co-evolution ability of SFLA. Furthermore, utilizing the mutation, crossover and collection processes of the difference evolution (DE) procedure to improve this hybrid system, the SWOA-based SFLA-WOADE model has been projected. Yang *et al*. [13] introduced a new hybrid chimp optimizer and hunger games search (ChOA-HGS) systems. In this model, at primary, the ChOA was utilized in order to select cluster head (CH) and professionally assembly clusters. Then, the HGS-based route method has been employed in order to define the system's best ways. The projected model integrates the advantages of routing and clustering, subsequent for optimum system period and energy efficacy.

Reddy *et al*. [14] developed an energy efficient cluster head (CH) assortment utilizing an improved version of the grey wolf optimization (EECHIGWO) procedure to ease the inequity among exploration and exploitation, absence of populace variety, and the early union of the simple GWO system. This technique reflects residual energy, sink distance, CH balance feature, and normal intra cluster space as the limits in choosing the CH. A struggle to coordinate and focus the underwater sensors instantaneously in a multi-hop atmosphere was measured [15]. This study recognized a link amid sensors point-to-point focused links followed by logically build the method for the organization as a utility of assortment, delay, and time stamps. Then, the method conveyed the unconstrained optimizer issue for localization by utilizing a gradient model. A system with compact and parallel models that is created on whale optimization algorithm (PCWOA) method is projected for enhancing effectiveness of the distance vector-hop (DV-Hop) [16]. The compact method keeps memory intake by decreasing the unique populace. Similar methods improve the capability to exits from local optimizer and enhance accurateness.

3. THE PROPOSED MODEL

In this article, we focus on design and development of the MCOANL-WSN technique. The main aim of the MCOANL-WSN algorithm is implemented for localizing the unknown nodes in the network using a metaheuristic optimization algorithm. Figure 1 demonstrates the workflow of MCOANL-WSN technique.

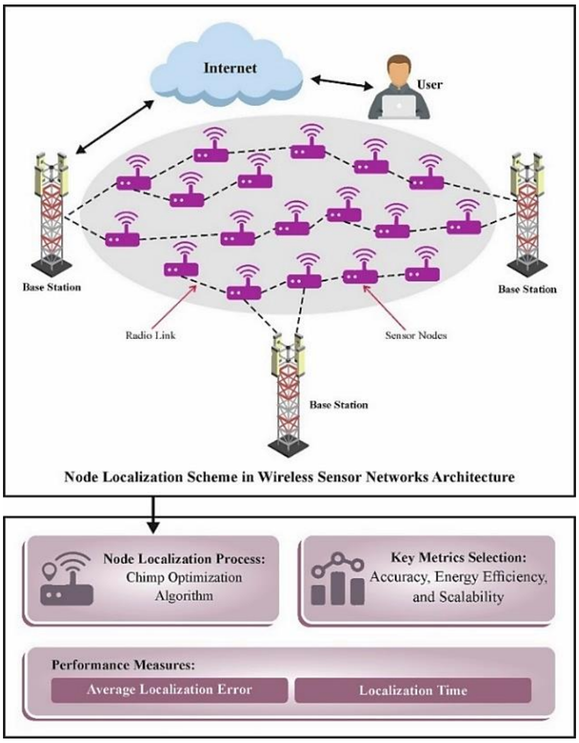

Figure 1. Workflow of MCOANL-WSN technique

3.1. Modeling of chimp optimization algorithm

Humans as well as chimpanzees have numerous similarities like DNA, social performances and intellectual aptitudes and these are prominent changes among them [17]. For instance, humans have more straight posture, a large brain, and less hair when compared with chimpanzees. Furthermore, humans have innovative mental skills like language, culture, and difficult problem resolving knowledge which are not present in chimpanzees. Technical sign proposes that chimpanzees can able to recognize definite mental procedures like vision but they do not observe views and others minds than humans.

Chimpanzees form difficult social clusters with a classified structure, robust bonds, and numerous social performances like grooming as well as communication. Current results recommend that they survive in a fission-fusion culture and display resemblances to humans that contains tool-making as well as supportive hunting. But struggles can rise and lead to violent performances and regional arguments. In addition, they have remarkable problem-cracking and cognitive skills, custom family elements as well as interrelating with nearby groups. In chimpanzee groups, chimp leader is the main individual who grips a dominant position within social hierarchy. The leader displays main behavior and plays a vital part in making decision, upholds social promises, solves fights, important in mating, and protects group's territory. The chimp leader's features safeguard existence and reproductive achievement of their group.

Chimpanzees are types of excessive attention due to their extraordinary connections, communication as well as aptitude. Their social performance and problem solving skills create them an attractive topic of research for scientists. There are 4 separate roles in chimpanzee societies that mentioned:

- Drivers are main chimpanzees that guide their group's actions and activities. They play a critical part in making decision and forming actions like leading group to victim.
- Chasers are alert and fast chimpanzees that shine in hunt and chasing performances. They are chiefly beneficial in chasing specific targets like prey during hunting.
- Barriers are robust and self-assured chimpanzees that defend their group. They generate barriers or problems to avert intruders or threats from entering group territory. Their main role is to safeguard their group and its territory.

– Attackers protect their group as well as employ their violent performance to predict the prey's escape way. They can send prey back near to hunters or down into the lower canopy.

Corresponding ChOA, we have 5 parts as:

a. Driving and chasing prey: technique of driving and chasing prey by chimps is defined. This behavior is expressed in (1) and (2), where d signifies distance among chimp and prey locations:

$$d = \left|c.x_{prey}(t) - m.xhimp(t)\right|, \tag{1}$$

$$x_{chimp}(t+1) = x_{prey}(t) - a.d. \tag{2}$$

here, t means existing iteration, $a, m,$ and c describes constant vectors, x_{prey} denotes prey position, and x_{chimp} means chimp position. The constants are calculated by employing (4) and (5):

$$\partial = 2fr_1 - f, \tag{3}$$

$$c = 2.r_2, \tag{4}$$

$$m = \ Chaotic; \tag{5}$$

multiple self-governing chimp clusters with dissimilar plans upgrade f for local and global hunts. This expands and balances search performance. f denotes key parameter in optimizer algorithm, flexible balance among exploitation and exploration. It monitors an algorithm's performance in exploring solutions and updated by using various plans for local and global hunts to enhance optimization. Liberated clusters improve exploration, balance global-local search, and grip difficult optimization. Chimps can able to change locations by employing random vectors. This procedure spreads to n-dimensional spaces. Chimps also utilize chaotic plans to attack prey, chaotic denotes state or performance described by chaos, which is a difficult and random pattern that looks casual but ruled by fundamental deterministic procedures.

b. Attacking technique (exploitation phase): chimps travel prey's position via driving, obstructive, chasing, and surrounding. Attacker chimps lead chasing that is mainly supported by drivers, barriers as well as hunter chimps. In (6)-(14) definite their interactions as (6)-(9):

$$d_{\text{Attacker}} = |c_1 x_{\text{Attacker}} - m_1 x| \tag{6}$$

$$d_{Barrier} = |c_2 x_{Barrier} - m_2 x| \tag{7}$$

$$d_{Chaser} = |c_3 x_{Chaser} - m_3 x| \tag{8}$$

$$d_{Driver} = |c_4 x_{Driver} - m_4 x| \tag{9}$$

upgrade positions is procedure of adjusting locations of chimp:

$$x_1 = x_{Attacker} - a_1(d_{Attacker}) \tag{10}$$

$$x_2 = X_{Barrie} a_2(d_{Barrier}) \tag{11}$$

$$x_3 = x_{Chaser} - a_3(d_{Chaser}) \tag{12}$$

$$x_4 = x_{Driver} - a_4(d_{Driver}) \tag{13}$$

overall upgraded position:

$$x(t+1) = \frac{x_1+x_2+x_3+x_4}{4} \tag{14}$$

c. Searching for prey (exploration): in last stage, chimps begin an attack when the prey stops its movement. In order to create a scientific method of this attack, we alter f value, which in turn restricts potential array for voting and becomes adjustable with random features within span of $[-2f, 2f]$, f

slowly decreases from 2.5 to 0 through iterations. The usage of random a value in $[-1, 1]$ tactically places chimp's next move among its present location and preys to ensure an effective attack 1. ChOA uses exact models to upgrade chimp positions based on attackers, barriers, chasers, and driver's positions to attack prey. But, to avert getting held in restricted solutions, extra methods needed to stimulate exploration. While driving, obstructive and chasing devices offer a grade of exploration. ChOA benefits from the combination of more techniques in order to increase this exploratory stage.

d. Prey attacking (utilization): at the time of exploration, chimps imitate attacker, barrier, chaser, and driver chimps' tracks to discover prey. They dissolve following random values ($> 1 or < -1$), helping global search by affecting away from the prey. The c value in ChOA in (4), random weights (0—2) to prey. It alters effect on distance in (5), improving stochastic performance and decreasing local least risks. c upholds chance over iterations where it is vital for exploration stage and pretends problems delaying prey pursuit. It adjusts prey's task affording to chimp's position.

e. Social incentive (sexual motivation): as described before, chimps fulfil their food and social requirements mainly via mating and grooming. So, their concentration moves away from chasing. ChOA employ of chaotic maps to increase ChOA and pretend their behaviors. Six maps utilized where all maps display deterministic as well as random behavior with a mutual point of 0:7. To take this united performance, a 50 percent prospect rules choice among normal position upgrades and chaotic methods through chimp position as (15):

$$x_{chimp}(t+1) = \begin{cases} x_{prey}(t) - a.d \ if \ \mu < 0.5 \\ Chaotic\_value \ if \ \mu \geq 0.5 \end{cases} \quad (15)$$

upgrade position typically when $\mu < 0.5$ and utilize chaotic value if $\mu \geq 0.5$ that μ is random in [0,1] and we estimate chaotic value by one of 6 maps.

3.2. Process involved in MCOANL-WSN method

The MCOANL-WSN algorithm includes the subsequent stages to identify the sensor in WSN. Randomly place N anchor node (AN) and M target nodes (TN) at the device portion [18]. Every AN was spatially localized and assisted for recognizing the position of alternative nodes. Each target and ANs encompass transmission range R.

– Distance among the ANs and TNs will be changed and estimated through protective Gaussian noise. The TN was employed to measure distance as $\hat{d}_i = d_i + n_i$ where d_i indicates the actual distance, viz., computed amongst the positions of TN (x, y) and Beacon (x_i, y_i):

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} \quad (16)$$

now, n_j controls the noise that follows the estimated distance in $d_i \pm d_i(P_n/100)$ and P_n means the sound connection with the predictable distance.

– The preferred node is named a NL when it proceeds 3 ANs at the CR of TN.

– For the NL, the MCOANL-WSN system could be individually performed for identifying the place of TN. The MCOANL-WSN model could be applied by the centroid of AN inside a CR:

$$(x_c, y_c) = \left(\frac{1}{N}\sum_{i=1}^{N} x_i, \frac{1}{N}\sum_{i=1}^{N} y_i\right) \quad (17)$$

we know that, N refers the total AN count in the transmission range of limiting TNs.

– The chaotic mapping lion optimization algorithm-based node localization approach (CMLOA-NLA) system has been applied for detecting the $(x, and\ y)$ coordinates as TN that reduced the localization error. The primitives utilized in localization problems describe 4-sided detachment amongst TN and AN:

$$f(x, y) = \frac{1}{N}\left(\sum_{i=1}^{N} \sqrt{(x - x_i)^2 + (y - y_i)^2} - \hat{d}\right)^2 \quad (18)$$

here $N \geq 3$ shows the AN counts stable a transmission radius of TN.

– While the highest repetition counts will be obtained, and followed by optimum location coordination (x, y) is determined by the MCOANL-WSN system. The localizing error has been determined after measuring the localizable TN N_L. This might be evaluated as a mean 4-sided of coldness in the node (X_i, Y_i) matches in coordinates of the real node (x_i, y_i):

$$E_1 = \frac{1}{N_1}\sum_{i=1}^{N}\sqrt{(x_i - X_i)^2 + (y_i - Y_i)^2} \quad (19)$$

– Stages 2-6 refers reiterated til the TN can localization. The localization model was dependent upon the mistake-control E_1, and the quantity of unlocalized prominences N_{N_L} is described as $N_{N_L} = M - N_L$. The decreased score of E_1 and N_{N_L} indicates a controlled method.

Finally, various methods for locating nodes in WSNs show important improvements in precision, energy saving, and flexibility, each providing specific advantages for different network situations and needs [19]-[22]. Additionally, the success of localization methods can be greatly affected by environmental conditions and the changing nature of sensor networks. For example, in cases where nodes experience movement or different communication settings, the reliability of these methods becomes crucial. Researchers are starting to look into hybrid methods that merge several localization techniques to improve accuracy adaptively in response to changing network structures [23]. These approaches not only tackle the challenges linked to fixed anchor locations but also further enhance energy use, as demonstrated by recent developments that use mobile anchors with conventional trilateration techniques. Furthermore, incorporating machine learning methods into localization tasks has been promising in boosting decision-making skills, facilitating real-time changes based on observed data trends, which could help lower localization mistakes even more. This shift towards adaptable and smart systems indicates a significant change in how WSNs tackle NL issues, opening up opportunities for more robust applications in various areas [24], [25].

4. EXPERIMENTAL VALIDATION

The localization results of the MCOANL-WSN technique can be investigated in terms of distinct measures. In Table 1 and Figure 2, a detailed average localization error (ALE) result of the MCOANL-WSN system is provided with recent ones [18]. The results imply that the modified gram Schmidt DV-Hop algorithm (MGDV-Hop) and WSN-DV-Hop models have shown worse results with increased ALE values. Next, the virtual partition and distance correction (VPDC) and elite oppositional farmland fertility optimization based node localization technique for wireless networks (EOFFONLWN) models have tried to exhibit slightly decreased ALE values. Although the CMLOA-NLA model has exhibited reasonable ALE value, the MCOANL-WSN technique highlighted its supremacy with least ALE values of 4.24%, 4.54%, 3.55%, 2.87%, 2.88%, 1.77%, and 1.32% under 5-35 Beacon nodes, correspondingly.

Table 1. ALE result of MCOANL-WSN model compared with other algorithms under various Beacon nodes

No. of Beacon nodes	WND-DV-Hop	MGDV-Hop	VPDC	EOFFONLWN	CMLOA-NLA	MCOANL-WSN
5	44.48	66.86	16.06	8.79	5.52	4.42
10	35.09	56.60	14.67	8.32	5.68	4.54
15	32.25	25.93	12.80	7.75	4.65	3.55
20	36.69	23.54	12.40	7.80	4.00	2.87
25	29.50	24.06	10.38	7.60	4.04	2.88
30	28.38	21.45	9.45	5.89	3.07	1.77
35	25.93	14.76	8.41	4.81	2.62	1.32

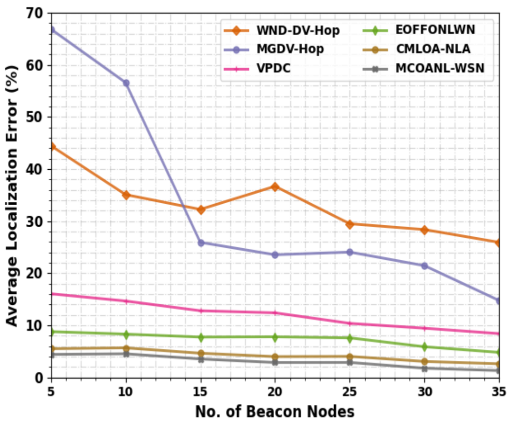

Figure 2. ALE outcome of MCOANL-WSN model under various Beacon nodes

A comprehensive localization time (LT) outputs of the MCOANL-WSN system was determined with recent methods in Table 2 and Figure 3. These accomplished outcome showcases that the MGDV-Hop and WSN-DV-Hop techniques are displayed poorer outcomes with improved LT values. Then, the VPDC and EOFFONLWN algorithms are closed to show moderately reduced localization error (LE) values. While the CMLOA-NLA method provides better LE value, the MCOANL-WSN system emphasized its excellence with least LT values of 0.105 min, 0.088 min, 0.111 min, 0.124 min, 0.138 min, 0.115 min, and 0.104 min based on 5-35 Beacon nodes.

Table 2. LT outcome of MCOANL-WSN system compared to other methods on number of Beacon nodes

No. of Beacon nodes	WND-DV-Hop	MGDV-Hop	VPDC	EOFFONLWN	CMLOA-NLA	MCOANL-WSN
5	0.980	2.906	0.418	0.370	0.201	0.105
10	0.939	2.838	0.440	0.357	0.179	0.088
15	0.863	2.613	0.468	0.378	0.226	0.111
20	0.868	2.369	0.514	0.375	0.244	0.124
25	0.849	2.529	0.511	0.408	0.239	0.138
30	0.845	2.462	0.554	0.426	0.243	0.115
35	0.854	2.321	0.550	0.396	0.230	0.104

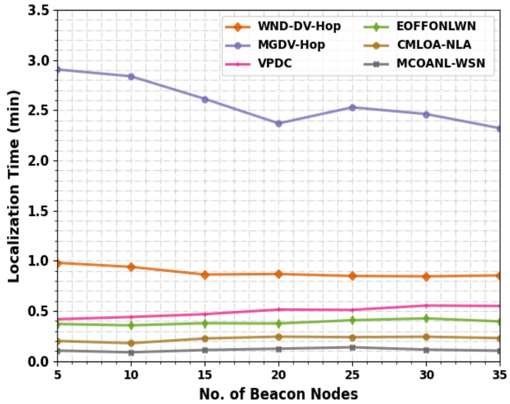

Figure 3. LT outcome of MCOANL-WSN algorithm with number of Beacon nodes

A wide-ranging ALE output of the MCOANL-WSN system can be measured with recent ones in Table 3 and Figure 4. These obtained outcome exhibits that the MGDV-Hop and WSN-DV-Hop methods are demonstrated the lowest outcomes with boosted ALE values. Meanwhile, the VPDC and EOFFONLWN algorithms offer moderately decreased ALE values. However, the CMLOA-NLA technique gains better ALE value, the MCOANL-WSN system underscored its superiority with lesser ALE values of 3.13%, 5.37%, 4.28%, 4.16%, 3%, 1.75%, and 0.40% in accordance with 5-35 m communication radius.

An extensive LT output of the MCOANL-WSN system can be evaluated with recent systems in Table 4 and Figure 5. These achieved findings exhibit that the MGDV-Hop and WSN-DV-Hop algorithms get decreased outcomes with increased LT values. Moreover, the VPDC and EOFFONLWN techniques are achieved moderately reduced LT values. But, the CMLOA-NLA method offers excellent LT value, the MCOANL-WSN technique highlighted its excellence with lowest L values of 0.204 min, 0.145 min, 0.100 min, 0.157 min, 0.097 min, 0.107 min, and 0.104 min based on 5-35 m communication radius. These values guaranteed the better performance of the MCOANL-WSN technique.

Table 3. ALE output of MCOANL-WSN technique compared with other systems under various communication radius

Communication radius (m)	WND-DV-Hop	MGDV-Hop	VPDC	EOFFONLWN	CMLOA-NLA	MCOANL-WSN
5	48.59	25.14	15.50	6.98	4.91	3.13
10	37.99	28.01	14.62	9.38	7.07	5.37
15	34.77	23.14	11.45	7.89	5.83	4.28
20	31.14	25.85	12.28	7.64	5.75	4.16
25	28.87	23.15	10.85	6.79	4.64	3.00
30	27.29	24.36	9.84	5.45	3.34	1.75
35	27.46	19.05	9.58	4.53	2.16	0.40

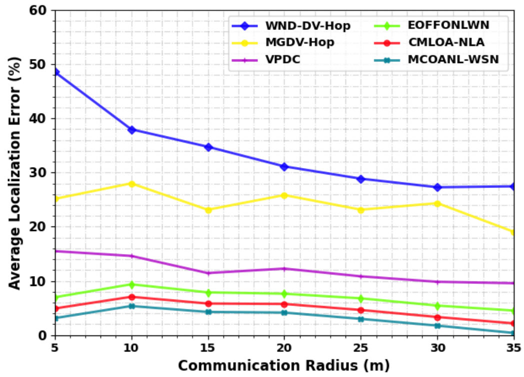

Figure 4. ALE outcome of MCOANL-WSN model under various communication radius

Table 4. LT outcome of MCOANL-WSN model compared to other techniques on diverse communication radius

Communication radius (m)	WND-DV-Hop	MGDV-Hop	VPDC	EOFFONLWN	CMLOA-NLA	MCOANL-WSN
5	1.288	2.464	0.558	0.456	0.276	0.204
10	1.002	2.415	0.546	0.477	0.267	0.145
15	0.941	2.395	0.553	0.433	0.229	0.100
20	0.887	2.393	0.539	0.421	0.238	0.157
25	0.799	2.356	0.501	0.405	0.191	0.097
30	0.747	2.352	0.506	0.417	0.213	0.107
35	0.685	2.409	0.464	0.395	0.228	0.104

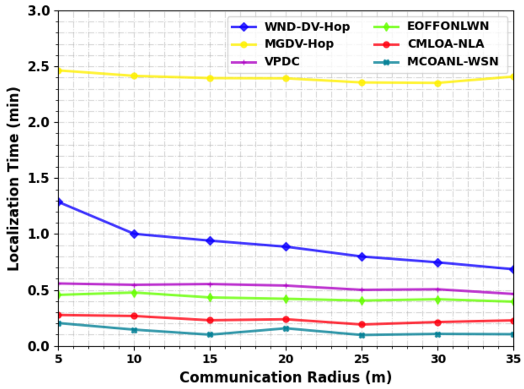

Figure 5. LT outcome of MCOANL-WSN system under various communication radius

5. CONCLUSION

In this article, we focuses on design and development of the MCOANL-WSN technique. The main aim of the MCOANL-WSN method is employed for localizing the unknown nodes in the network using metaheuristic optimization algorithm. The MCOANL-WSN method implements a modeling architecture that incorporates the distinctive features of COA, recognized for its stimulation from the cooperative hunting behavior of chimpanzees, into the NL procedure. Additionally, the COA-based localization model is considered for adapting dynamically to the resource-constrained and dynamic type of WSNs. The performance of the MCOANL-WSN system can be measured via wide-ranging simulations, considering crucial metrics like scalability, energy efficiency, and localization accuracy. The results prove the superiority of the developed modeling technique over existing NL schemes, showcasing its capability to improve the overall reliability and efficiency of WSNs in different applications.

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