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Modeling of Dung Beetle Optimization-based Sink Node Localization Approach for Wireless Sensor Networks

R. Padmaraj*[1], K. Selvakumar[2]

[1,2] Department of Information Technology, Annamalai University, Annamalainagar – 608002, Tamil Nadu, India

Emails: thillaikoothan@gmail.com; kskaucse@gmail.com

Abstract

Wireless sensor network (WSN) performs monitoring of each aspect of the area of interest by detecting the surrounding physical phenomena with sensor nodes and transferring the information to the gateway through the corresponding system. Several researcher workers have introduced localization methods to accomplish high accuracy of localization. An intelligent optimization technique has attracted various researcher workers due to its advantages such as strong optimization capability and few parameters to optimize the localization performance of the DV-Hop method. Sink node localization (NL) using metaheuristics in WSN includes applying optimization techniques inspired by human behavior or natural phenomena to define the geographical coordinates of the sink nodes within the network coverage region. WSNs can accomplish better localization performance, especially in dynamic or complex environments, improving the efficiency and reliability of network management and data transmission by leveraging metaheuristics. In this view, this manuscript develops a Dung Beetle Optimization based Sink Node Localization Approach (DBO-SNLA) for WSN. In the DBO-SNLA technique, the DBO algorithm involved is based on the social behavior of dung beetle populations and is developed with five updated rules to assist in finding high-quality solutions. In addition, the DBO-SNLA technique addresses the issues of defining the sink node location with lowest localization error once the data between the nodes is transferred wirelessly. Finally, the localization errors are calculated and the location of the different unknown nodes is computed. A detailed set of simulation takes place to examine the performance of the DBO-SNLA technique. The empirical analysis stated the betterment of the DBO-SNLA method than other techniques

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1. Introduction

Wireless Sensor Network (WSN) plays a vital part in Internet of Things (IoT), which are utilized in numerous profits all over the world like volcano and fire monitoring, and urban sensing, to discover rare animals and perimeter surveillance [1]. In the WSN, a sink is defined as an entity which gathers data from the sensors in the sensing area. With the growth of 3G phones, mobile PDAs and other handheld gadgets, many applications want to combine sink nodes [2]. With the aid of these devices, mobile sink is wanted to fulfil the necessity. A mobile sink can potentially endure the network's lifetime by utilizing lower energy of the sensor nodes nearby to sink owing to its altering locations [3].

Network connectivity is a vital concern in WSN, which has attracted researchers' attention for years, mainly concentrating on tactics to attain or uphold full connectivity for communication in different uses [4]. For full connectivity, there occurs single transmission path linking any set of nodes. Furthermore, a network was assumed as k-connected if the exclusion of any $(k-1)(k-1)$ sensor doesn't reduce the detached network [5]. But the sensor isolation is not an omission but quite familiarity in practice. The main causes contain, but are not restricted to, load variants, unbalanced energy consumption, non-uniform data communication, dissimilar sensor abilities, and much more [6]. Therefore, inspecting the assets of an incompletely linked WSNs and monitoring the inter-relationship among network performance.

Besides, the present works on connectivity analysis and communication mostly concentrate on ad hoc network methods whereas each nodes were preserved as equal [7]. The vital and exclusive part of the sink nodes, liable for data fusion and collection, which hasn't got the consideration it earns in delay-sensitive, data-centric, fault-tolerant, and power-restricted WSNs [8]. In order to be precise, the status of sensor's connection is based on its capability to create a path to grasp the sink nodes for the data aggregation. Distinct from ad hoc network, a WSN was considered distinct, when the sink node does not fit the massive associated modules [9]. Since the real-world sink node situation is frequently limited by environmental features, it is vital to deliver the sink nodes distinctly and reflect the position of a random WSN in numerous scenarios [10].

Gumaida and Ibrahim [11] projected a new and severe efficacy localization technique using a simplex optimizer model for node localization (NL). This technique is a straight search model and is generally focused on resolving non-linear optimizer issues, and it is named the Nelder-mead Method (NMM). It is recommended that the function of objective that is enhanced utilizing NMM is the MSE of all neighbouring ANs connected in WSN. This work highlights using a fluctuating model named RSSI to estimate the distance amongst every node of WSN. Kooshari et al. [12] projected an optimum routing model in order to decrease consumption of energy in WSN. Initially, WSNs are gathered through the Water strider algorithms (WSA), and CHs are nominated for the data tranmission. Next, a mobile sink gathers the data from the CHs and transmits it to the BS. The mobile sink utilizes ACO methods in order to portable a smaller path among the CHs. The authors donate to offering a separate type of WSA model. Krishna et al. [13] projected a Genetic Lavrentyev Paraboloid Lagrange SVM-based (GLPL-SVM) multi-class classification technique. The approach contains Paraboloid Lagrange Multiplier SVM-based multi-class Classification for the network coverage, GL Regularized ML-based Node Deployment for the SN localization, and Quadrant Count Event-based Data Aggregation for effective collection of data.

In [14], projected a path development model for WSN depends upon the mixture of map-matching technique and double-pole search technique. The map-matching system is utilized in order to compute the optimum sample node quantity of the information transmission. The DPS technique is utilized based on optimum sample node quantity in looking out every SN of the path, and dual clusters of path plans were attained. Racharla and Jeyaraj [15] developed a new technique of NL. Particularly, an effectual localization system is projected for WSN by calculating the movement portion between the anchor and non-anchor nodes by originating the function of objective. As the identified location of ANs in WSNs, it helps discover the positon of unknown nodes utilizing a hybrid optimizer method. Likewise, the Modernized Position-based Glowworm and Cat Swarm Optimizer (MP-GCSO) technique is utilized. After assigning the location, the best locations are achieved by the highest hop counts utilizing the hybrid method.

In [16], the Seagull optimizer algorithm (SOA) and its improved types were useful to upsurge the accuracy of NL. The chaotic maps and levy flight are utilized to improve the randomness and accuracy of SOA. Also, the chaotic map-based SOA (C-SOA) and the LF-SOA are employed for the node position in WSN. Asvial et al. [17] proposed Division Non-Cooperative Game LEACH (DivNCGL) routing model by allocating the CHs. By separating the distribution region into sub-regions, the distribution procedure was executed. The sub-region division procedure utilizes the possibility value attained through the non-cooperative game technique based on the total residual energy (RE), the energy needed for spread and the residual active nodes.

This manuscript develops a Dung Beetle Optimization-based Sink Node Localization Approach (DBO-SNLA) for WSN. In the DBO-SNLA technique, the DBO algorithm involved is based on the social behavior of dung beetle populations and is developed with five updated rules to assist in finding high-quality solutions. In addition, the DBO-SNLA technique addresses the issues of defining the sink node location with lowest localization error once the data between the nodes is transferred wirelessly. Finally, the localization errors are calculated and the location of the different unknown nodes is computed. A detailed set of simulation analyses takes place to examine the performance of the DBO-SNLA technique.

2. Background Information

The energy consumed by CH is given below [18]:

1. The SNs are positioned arbitrarily in the 2D space.
2. The BSs are situated at the network and there is multihop transmission from CHs to the BSs.
3. The SNs are broken down into almost identical groups, and dispersed arbitrarily.
4. The SNs are homogeneous and the mobility is constrained to 0.2 m/s.

5. BSs and the nodes that contribute to multihop transmission have continuous energy sources.
6. BS performs the approach for the CHS and it collects information from the CHs.

The free space path loss (d^2) for the single-hop transmission and multi-path transmission fading (d^4) model for the multi-hop path transmission is the radio energy model of SNs. Thus, the power utilization for transferring n-bit packets through distance $'d'$ is calculated by Eq. (1):

$$E_{TX}(n,d) = \begin{cases} nE_{elec} + ne_{fs}d^2 & d < d_0 \\ nE_{elec} + ne_{mp}d^4 & d \geq d_0 \end{cases} \quad (1)$$

Where e_{fs} and e_{mp} → energy dissipation coefficient of free-space and multipath attenuation mechanism, n → packet length, d → distance between sending and receiver nodes, $d_0 = \sqrt{e_{fs}/e_{mp}}$ → threshold distance, and E_{elec} → energy required for transmitting or receiving 1-bit data.

At Rx, the quantity of power consumed for receiving n-bit data packets is calculated by the following expression:

$$E_{RX}(n) = n \times E_{elec} \quad (2)$$

The data gathered by CH, amount of gathered packets transported from CHs to BSs, and amount of data packets received from SNs which are members of specific clusters are the three parameters contributing to the power consumption at CH.

$$E_{CH} = E_{RX}(n,d) \times SN_{num} + E_{DF} \times n \times (SN_{num} + 1) + E_{TX}(n,d) \quad (3)$$

SN_{num} → $SN's$ Count in a certain cluster. E_{DF} →data fusion energy.

The power consumed is $E_{TX}(n,d)$ for each SNs except CHs.

The overall RE at the k^{th} round is given as:

$$E_R(k) = E_R(k-1) - \left(\sum_{l=1}^{CH_{num}(l)} E_{CH}\,(l) + \sum_{m=1}^{SN_{alive}(k)-CH_{num}(k)} E_{SN}\,(m) \right) \quad (4)$$

$E_R(k-1)$ → overall RE at $(k—l)^{th}$ iteration, $CH_{num}(k)$ → CHs count at k^{th} iteration, $SN_{alive}(k)$ → overall alive node count at k^{th} iteration, $E_{CH}(1)$ → power consumption by 1^{th} CH, and $E_{CH}(m)$ → power consumption by m^{th} SN

3. Proposed Methodology

In this manuscript, we have developed a novel DBO-SNLA approach for WSN. The main purpose of DBO-SNLA approach comprises two different stages involved as demonstrated in Fig. 1.

A. Stage I: Algorithmic Design of DBO

In their natural habitat, dung beetles (DBS) confront the problem of keeping straight course while rolling the dung balls [19]. The position updating of rolling dung beetle is given below.

$$x_i(t+1) = x_i(t) + a \cdot k \cdot x_i(t-1) + b \cdot \triangle x$$
$$\triangle x = |x_i(t) - X^{worst}| \quad (5)$$

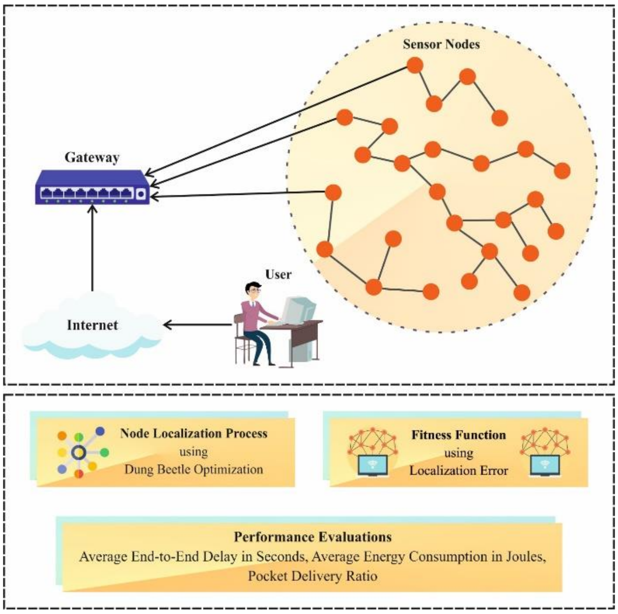

Figure 1: Overall process of DBO-SNLA approach

In Eq. (5), t refers to the existing iteration counter, $x(t)$ denotes the dung beetles location at t^{th} iteration. The parameter a is at what degree natural factors, namely wind and terrain, cause dung beetles to depart from the original direction. If $a = 1$, then there is no deviation, if $a = -1$ then it deviates from the original direction. The k variable is constraint within the range of $(0{,}0.2]$, describes the defect factor and is fixed as 0.1. b is a constant value in the interval $[0,1]$, and set to 0.3. X^{worst} indicates the global worst values, $\triangle x$ simulates the effect of solar illumination, with the greater $\triangle x$ representing a great distance between the light source and the dung beetle.

In the wild, the dung beetles change their rolling trajectory through reminiscent behaviors of dance when confronted with impediments. To emulate these characteristics, the study presented a probability model to encounter difficulties during the transportation of dung balls. The tangent function defines the revised trajectory upon encountering such impediments, which captures the complex adjustments like the dance movement of dung beetles.

$$x_i(t+1) = x_i(t) + \tan(\theta)|x_t(t) - x_i(t-1)| \tag{6}$$

i) Spawning Dung Beetles

In the wild, dung beetle shows intelligent behavior in selecting optimum location for spawning. To simulate this, the study presents an approach for boundary delineation to define the area as follows:

$$Lb^* = \max(X^{best1} \times (1-R), Lb)$$
$$Ub^* = \min(X^{best1} \times (1-R), Ub) \tag{7}$$

The lower and upper boundaries of the spawning region are represented as Lb and Ub, correspondingly, X^{besi1} indicates the present local optima. The R parameter is calculated by $R = 1 - t/\text{Tmax}$, $Tmax$ denotes the maximal iteration count. Upon finding the optimum spawning area, the dung beetles quickly initiate spawning within it. The ever-evolving dynamics of spawning area ensure continuous exploration of the neighborhood near the exiting optimum solution, thus avoiding a local optima solution.

$$x_i(t+1) = X^{best1} + b_1 \times (x_i(t) - Lb^*) + b_2 \times (x_i(t) - Ub^*) \tag{8}$$

Where b_1 and b_2 are random parameters with dimension of $1 \times Dim$, where Dim denotes the dimensionality problem.

ii) Foraging Dung Beetles

In nature, dung beetles engaged in foraging behaviors indicative of choosing a secure location.

$$Lb^b = \max(X^{best2} \times (1-R), Lb)$$

$$Ub^b = \min(X^{besi2} \times (1 - R), Ub) \quad (9)$$

Where X^{best2} represents the optimum global location, Lb^b and Ub^b are the lower and upper limitations of the optimum foraging region, correspondingly. Lb and Ub are the lower and upper limitations for the solution space. The foraging activity performed by the dung beetles corresponds to the location updating.

$$x_i(t+1) = x_i(t) + C_1 \times (x_i(t) - Lb^b) + C_2 \times (x_i(t) - Ub^b) \quad (10)$$

Where C_1 refers to the normal distribution random number, and C_2 is a vector of size $1 \times Dim$, within [0,1]. Fig. 2 represents the flowchart of DBO.

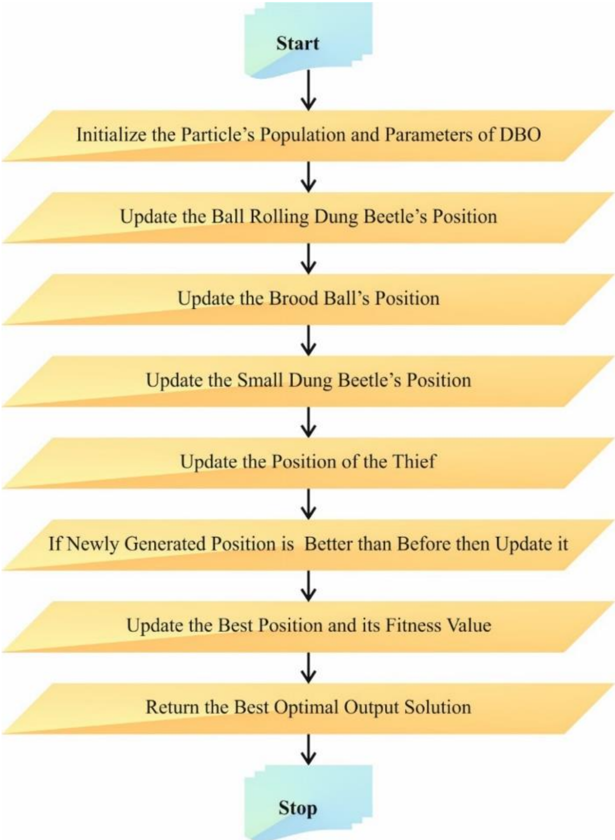

Figure 2: Flowchart of DBO

iii) Stealing Dung Beetles

In their natural habitat, dung beetles engaged in the activity of stealing dung balls from conspecifics. To stimulate this, the study devises the global optimum location Xb as the location of the contested dung balls.

$$x_i(t+1) = X^{best2} + S \cdot g \cdot (|x_i(t) - X^{best1}| + |x_i(t) - X^{best2}|) \quad (11)$$

Where S denotes the constant with the predefined value of 0.5. The g parameter denotes the magnitude of random parameter, Dim represents the dimensionality of problem.

B. Stage II: Steps involved in DBO-SNLA technique

The NL estimation gradient error mechanism assists in dissipating energy to allow information and transmit the packets to the BS within the size of 100 by 100, considering the 10% of the overall SNs for the anchor node which is labelled as the CHs [20]. The hop count is fixed as 0 where the (Xi, Yi) with the anchor node identities (i) and Hop_{ij} is considered as the hop counts that are transmitted to the BSs. The presented method tries to find the solution as follows:

Step 1. Set the criteria for network.

Step 2. Homogeneous energy for each SN as

$$E_{Total} = \sum_{i=1}^{n} E_0\,(1 + a_i) = E_0\left(\left(n + \sum_{i=1}^{n} a_i\right)\right) \tag{12}$$

Step 3. Begin iteration of the calculation of p_i for heterogeneous nodes as

$$p_i = \frac{p_{opt}N(1 + a)E_i(r)}{(N + \sum_{i=1}^{N} a_i)\overline{E}(r)} \tag{13}$$

a. Compute the energy required by the transmitting amplifier

$$E_{TX}(1, d) = \begin{cases} lE_{elec} + l\varepsilon_{f_s}d^2, & d \geq d_0 \\ lE_{elec} + l\varepsilon_{mp}d^4, & d < d_0 \end{cases} \tag{14}$$

And the calculation of power required by the receiver as

$$E_{RX}(l) using E_{RX}(l) = E_{elec} \tag{15}$$

Step 4. Compute

$$(AvgHopSize_i) \tag{16}$$

Step 5. The average size of Hop for the distance between the SNs is given as

$$AvgHopSize_i = \frac{\sum_{j=1\ j\neq 1}^{m} \sqrt{(X_j - X_i)^2 + (y_J - y_i)^2}}{\sum_{j=1\ j\neq i}^{m} H\ opij} \tag{17}$$

Step 6. Compute the average Hop size, where u and I are variables and j is constant

$$d_{iu} = AvgHopSize_j \times hop_{iu} \tag{18}$$

Step 7. The weighted centroid technique for the SN localization as m is defined as an anchor' node for the overall (X_u, Xy_u), m denotes the overall anchor node count.

$w_i = \frac{1}{mHop_{ui}}$ is the weighted factor for i and the SNs are not known as

$$X_u = \frac{\sum_{i=1}^{m} w_{ix_i}}{\sum_{i=1}^{m} w_i}, y_u = \frac{\sum_{i=1}^{m} w_{iy_i}}{\sum_{i=1}^{m} w_i} \tag{19}$$

Step 8. The Wi factor for the SNs for unknown SNs is localized

$$w_i = \frac{\sum_{i=1}^{m} H\ op_{ui}}{mHop_{ui}} \tag{20}$$

Step 9. Consider the anchor node count as CHs to be q, matrix A characterizes the power consumed by all the nodes selected as CH and q denotes the CH count. aij indicates the power consumption of i CH which is typical node if j CH is its CHS. Furthermore, b_i represents the RE of CH i, whereas xi states the times that CH i becomes a CH. Thus, B and X are matrices, so that $A \cdot X = B$, as follows:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & & a_{1k} \\ a_{21} & a_{22} & a_{23} & \cdots & a_{2k} \\ a_{31} & a_{32} & a_{33} & & a_{3k} \\ & \vdots & & \ddots & \vdots \\ a_{k1} & a_{k2} & a_{k3} & \cdots & a_{kk} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_k \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \vdots \\ b_k \end{bmatrix} \tag{21}$$

The code snippet computes the round number within the network to attain the optimum cluster count

Step 11. The localization errors are calculated and the evaluated location of the unknown node is evaluated.

$$\frac{1}{n \times r} \sum_{i=1}^{n} \frac{Guass\ localization\ error =}{\sqrt{(X_{ai} - X_{ui})^2 + (y_{ai} - y_{ui})^2}} \tag{22}$$

4. Experimental Validation

The experimental validation of the DBO-SNLA technique is given. In Table 1 and Fig. 3, the average end-to-end delay (AETED) outcomes of the DBO-SNLA method are compared with other techniques [21]. The outcomes specify the supremacy of the DBO-SNLA model with minimum AETED values. With speed of 10m/s, the DBO-SNLA approach provides least AETED of 0.017s whereas the RDCM, VELCT, MBC, and ESWCA techniques attain maximum AETED of 0.030s, 0.082s, 0.083s, and 0.101s, correspondingly. Additionally, with speed of 30m/s, the DBO-SNLA approach provides minimum AETED of 0.022s whereas the RDCM, VELCT, MBC, and ESWCA techniques attain maximum AETED of 0.032s, 0.084s, 0.086s, and 0.095s, correspondingly. Additionally, with speed of 50m/s, the DBO-SNLA approach proves least AETED of 0.022s whereas the RDCM, VELCT, MBC, and ESWCA techniques attain maximum AETED of 0.033s, 0.086s, 0.088s, and 0.095s, correspondingly.

Table 1: AETED analysis of DBO-SNLA method with existing techniques under varying speeds

Average end-to-end delay in seconds					
Speed in (m/s)	DBO-SNLA	RDCM	VELCT	MBC	ESWCA
10	0.017	0.030	0.082	0.083	0.101
20	0.021	0.032	0.082	0.084	0.097
30	0.022	0.032	0.084	0.086	0.095
40	0.022	0.034	0.084	0.088	0.096
50	0.022	0.033	0.086	0.088	0.095

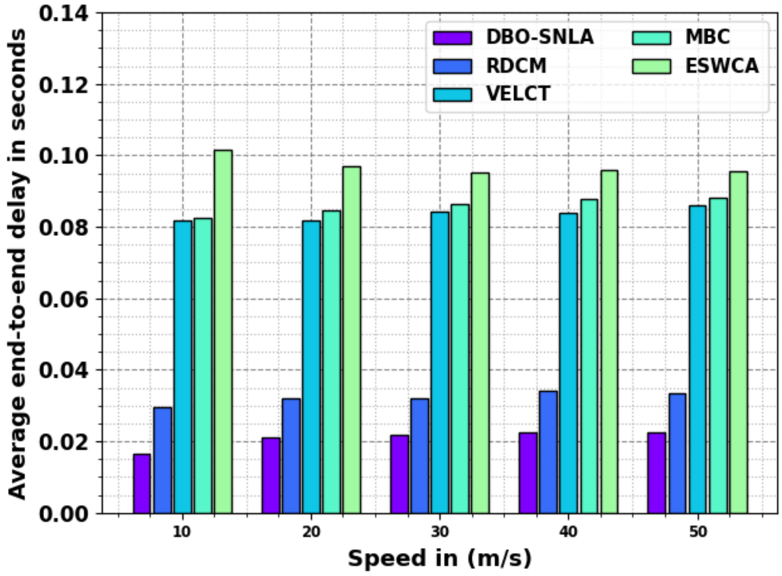

Figure 3: AETED analysis of DBO-SNLA method under various speeds

In Table 2 and Fig. 4, the average energy consumption (AECON) results of the DBO-SNLA technique are compared with other approaches. The outcomes represent the supremacy of the DBO-SNLA method with lower AECON values. With speed of 10m/s, the DBO-SNLA method provides least AECON of 1.995J whereas the RDCM, VELCT, MBC, and ESWCA techniques attain maximum AECON of 2.090J, 2.293J, 2.381J, and 2.440J, correspondingly. Additionally, with speed of 30m/s, the DBO-SNLA approach provides least AECON of 2.063J whereas the RDCM, VELCT, MBC, and ESWCA techniques attain maximum AECON of 2.210J, 2.436J, 2.608J, and 2.743J, correspondingly. Additionally, with speed of 50m/s, the DBO-SNLA approach provides least AECON of 2.127J whereas the RDCM, VELCT, MBC, and ESWCA methods attain maximum AECON of 2.265J, 2.618J, 2.687J, and 2.796J, correspondingly.

Table 2: AECON analysis of DBO-SNLA method with existing techniques under varying speeds

Average energy consumption in joules					
Speed in (m/s)	DBO-SNLA	RDCM	VELCT	MBC	ESWCA
10	1.995	2.090	2.293	2.381	2.440
20	2.058	2.170	2.379	2.526	2.689
30	2.063	2.210	2.436	2.608	2.743
40	2.089	2.246	2.535	2.632	2.784
50	2.127	2.265	2.618	2.687	2.796

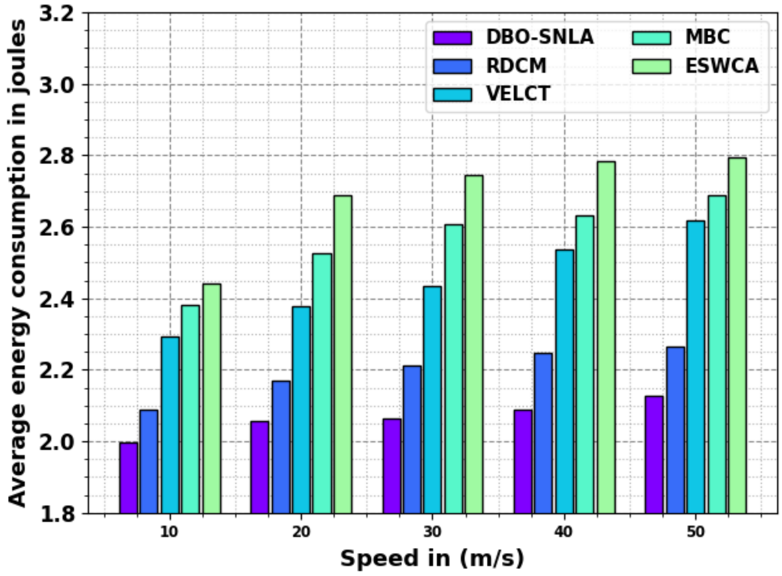

Figure 4: AECON analysis of DBO-SNLA method under varying speeds

The comparative packet delivery ratio (PDR) results of the DBO-SNLA system are reported in Table 3 and Fig. 5. The outcomes emphasized that the ESWCA method has shown ineffectual performance over other techniques. Additionally, the MBC method has obtained slightly increased PDR values. Even though the RDCM and VELCT approaches have resulted in closer PDR values, the DBO-SNLA method highlighted maximum PDR values of 99.52%, 98.21%, 97.55%, 96.33%, and 95.22% under speed limit of 10-50m/s, correspondingly.

Table 3: PDR analysis of DBO-SNLA method with existing techniques under varying speeds

Pocket delivery ratio (%)					
Speed in (m/s)	DBO-SNLA	RDCM	VELCT	MBC	ESWCA
10	99.52	98.23	91.49	89.11	79.91
20	98.21	96.80	89.38	87.61	79.98
30	97.55	95.51	87.74	87.13	79.23
40	96.33	94.42	87.13	85.22	78.69
50	95.22	91.42	86.52	84.07	76.98

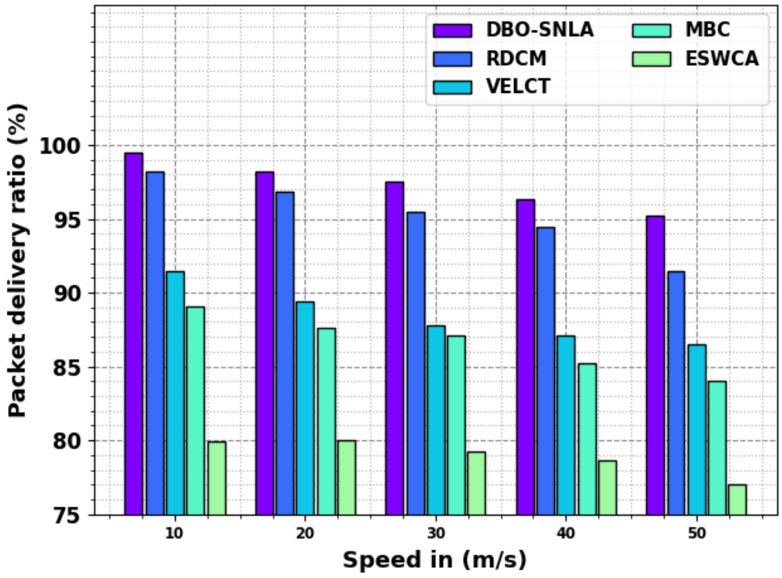

Figure 5: PDR analysis of DBO-SNLA technique under various speeds

In Table 4 and Fig. 6, the AECON outcomes of the DBO-SNLA method are compared with other techniques under node counts. The outcomes specify the supremacy of the DBO-SNLA method with minimum AECON values. With 100 nodes, the DBO-SNLA approach provides minimum AECON of 1.105J whereas the RDCM, VELCT, MBC, and ESWCA techniques attain maximum AECON of 1.348J, 1.418J, 1.506J, and 1.682J, correspondingly. Additionally, with 300 nodes, the DBO-SNLA method provides minimum AECON of 1.219J whereas the RDCM, VELCT, MBC, and ESWCA techniques attain maximum AECON of 1.441J, 1.611J, 1.633J, and 1.704J, correspondingly. Furthermore, with 500 nodes, the DBO-SNLA method provides minimum AECON of 1.297J whereas the RDCM, VELCT, MBC, and ESWCA approaches attain maximum AECON of 1.535J, 1.686J, 1.737J, and 1.743J, correspondingly.

Table 4: AECON analysis of DBO-SNLA method with existing techniques under node counts

Average energy consumption in joules					
Number of nodes	DBO-SNLA	RDCM	VELCT	MBC	ESWCA
100	1.105	1.348	1.418	1.506	1.682
200	1.179	1.372	1.519	1.593	1.693
300	1.219	1.441	1.611	1.633	1.704
400	1.240	1.519	1.660	1.689	1.725
500	1.297	1.535	1.686	1.737	1.743

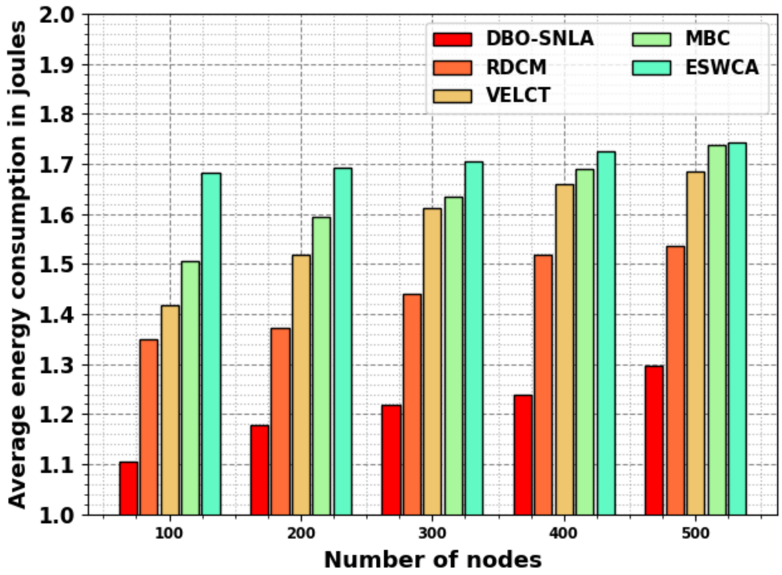

Figure 6: AECON analysis of DBO-SNLA technique under various nodes

In Table 5 and Fig. 7, the AETED outcomes of the DBO-SNLA method are compared with other techniques under node counts. The outcomes specify the supremacy of the DBO-SNLA approach with minimum AETED values. With 100 nodes, the DBO-SNLA method provides minimum AETED of 0.019s whereas the RDCM, VELCT, MBC, and ESWCA approaches attain maximum AETED of 0.029s, 0.084s, 0.087s, and 0.097s, correspondingly. Additionally, with 300 nodes, the DBO-SNLA method provides minimum AETED of 0.020s whereas the RDCM, VELCT, MBC, and ESWCA approaches attain maximum AETED of 0.032s, 0.083s, 0.087s, and 0.099s, correspondingly. Additionally, with 500 nodes, the DBO-SNLA technique provides minimum AETED of 0.019s whereas the RDCM, VELCT, MBC, and ESWCA methods attain maximum AETED of 0.030s, 0.086s, 0.089s, and 0.102s, correspondingly.

Table 5: AETED analysis of DBO-SNLA method with existing techniques under nodes counts

Average end-to-end delay in seconds					
Number of nodes	DBO-SNLA	RDCM	VELCT	MBC	ESWCA
100	0.019	0.029	0.084	0.087	0.097
200	0.021	0.031	0.084	0.088	0.098
300	0.020	0.032	0.083	0.087	0.099
400	0.022	0.031	0.084	0.087	0.099
500	0.019	0.030	0.086	0.089	0.102

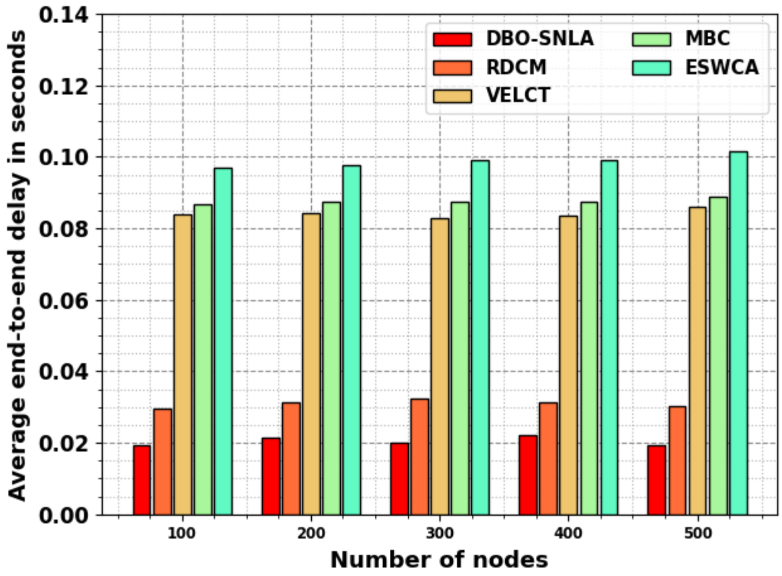

Figure 7: AETED analysis of DBO-SNLA technique under varying nodes

The comparative PDR outcomes of the DBO-SNLA method are shown in Table 6 and Fig. 8. The outcomes indicated that the ESWCA approach has demonstrated ineffectual performance over other models under node counts. Moreover, the MBC techniques have attained slightly increased PDR values. Even though the RDCM and VELCT approaches have resulted in closer PDR values, the DBO-SNLA method emphasized superior PDR values of 99.27%, 98.90%, 98.55%, 98.36%, and 97.95% under nodes of 100-500, correspondingly.

Table 6: PDR analysis of DBO-SNLA method with existing techniques under varying nodes

Pocket delivery ratio (%)					
Number of nodes	DBO-SNLA	RDCM	VELCT	MBC	ESWCA
100	99.27	98.16	92.29	91.57	81.94
200	98.90	97.63	90.97	90.25	81.48
300	98.55	97.30	90.25	89.13	81.81
400	98.36	97.10	89.52	87.94	80.03
500	97.95	97.04	89.19	87.15	79.10

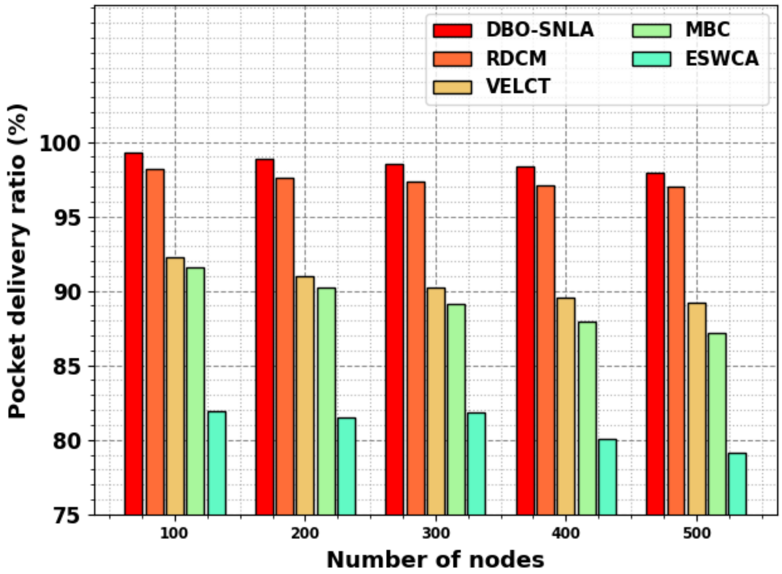

Figure 8: PDR analysis of DBO-SNLA method under varying nodes

5. Conclusion

In this manuscript, we have developed a novel DBO-SNLA approach for WSN. In the DBO-SNLA technique, the DBO algorithm is involved, which is inspired by the social behavior of dung beetle populations and is developed with five update rules to assist in finding high-quality solutions. In addition, the DBO-SNLA technique addresses the issues of defining the sink node location with minimum localization error once the data between the nodes is wirelessly transferred. Finally, the localization error is calculated and the estimated location of the different unknown nodes is estimated. A detailed set of simulation analyses takes place to examine the performance of the DBO-SNLA technique. The experimental outcomes stated the supremacy of the DBO-SNLA technique compared to other models.

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