Efficient Sink Node Position Estimation using Harris Hawks Optimization Algorithm in Wireless Sensor Networks

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Abstract

Wireless sensor network (WSN) was utilized widely in numerous areas owing to their accessibility in data collection, processing, and transmission, and the strength and reliability of data processing and transmission are based on the accuracy of the positions of sensor nodes (SNs) in the WSN. Sink node location estimation in WSN is a vital task intended to define the geographical position of the sink node in the network area of coverage. This procedure normally includes using numerous localization techniques that trust data like received signal strength, arrival time, time variance of arrival, or angle of arrival from adjacent SNs. The accuracy of sink node localization directly influences the efficiency of data aggregation, routing procedures, and complete performance of the network in tasks like environmental monitoring, target tracking, and event recognition. As WSNs are frequently used in remote environments where physical involvement is unusable, an effective and accurate sink node localization model plays a vital part in certifying the network's longevity and reliability. This study develops an Efficient Sink Node Position Estimation using the Harris Hawks Optimization (SNPE-HHO) Algorithm in WSN. The main intention of the SNPE-HHO technique is to recognize the optimal position of the sink node in the network. To achieve this, the SNPE-HHO technique employs the HHO system which gets inspiration from the hunting tactics of Harris Hawk. Moreover, the SNPE-HHO technique computes a fitness function that can drive the searching direction of the HHO algorithm and enhance the node estimation performance. The performance analysis of the SNPE-HHO method is verified by utilizing distinct metrics. The experimentation values confirmed the improved estimation performance of the SNPE-HHO technique over other existing methods

Keywords: Internet of Things; Wireless Sensor Network; Harris Hawks Optimization; Sink Node; Fitness Function

1. Introduction

The Internet of Things (IoT) is one of the developing technologies that contain energy to modify our outlook [1]. The assurance of this technology makes it the most effective area of research, defending its performance features. In this context, the work takes place and whose target is to enhance the communication in the IoT network [2]. In our opinion, the communication and device portion of an IoT method is a straight descending of Wireless Sensor Network (WSN), in the intellect which is resource-constrained, networked methods mostly concentrating on low-power devices of wireless [3]. Numerous IoT networks show exclusive features and also have a few significant limits like computational power, memory, and energy. Energy is a restraint of excessive significance for the life-time of the WSN, and, as a significance, the complete system based on it [4]. The power restrictions limit computational power and nodes' memory. One of the chief standards in designing a WSN application is extending the network lifetime and averting connectivity degradation over violent energy management. There is a trade-off among a node range, node's energy, cost, and size [5]. Owing to the necessity to preserve battery lifetime, the sensor nodes work with lower-duty series and communicate occasionally, over short spaces with lower data rates. In WSN, from nodes to sink, the flow of data is mainly unidirectional [6]. The non-renewable power supply,

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restricted resources, and short radio propagation distance of sensor nodes execute restraints on applications of WSN not originating in wired networks.

Owing to the upsurge in applications of IoT, numerous issues have developed in the network. The communication model of hop-by-hop from nodes to sink and the restricted energy power are the foremost causes of the issues. As an outcome, the system may suffer from energy holes that outcome in congestion or system partitioning [7]. A method for resolving these issues is the usage of mobile elements in the system. Mobile elements are capable of altering their location in the IoT network [8]. A technique that utilizes mobile elements which generally uses dual strategies. Mobile nodes can change around the system and gather information from nodes on the spot. This method diminishes the issue of network interruption owing to the consumption of energy [9]. In contrast, the employ of mobile nodes (MNs), with parallel features as static nodes, helps present nodes in executing their challenges, both by substituting energy-drained nodes or by generating substitute trails to the sink. A method that bases their process on mobile sinks, increases the life-time of the system [10]. Then, techniques that utilize MNs want to take into concern the energy consumption method in usage.

This study develops an Efficient Sink Node Position Estimation using the Harris Hawks Optimization (SNPE-HHO) Algorithm in WSN. The main intention of the SNPE-HHO technique is to recognize the optimal position of the sink node in the system. In order to achieve this, the SNPE-HHO system uses the HHO system which drives stimulation from the hunting tactics of Harris Hawk. Moreover, the SNPE-HHO technique computes a fitness function that can direct the searching path of the HHO algorithm and enhance the node estimation performance. The performance study of the SNPE-HHO method is verified utilizing distinct metrics.

2. Related Works

In [11], a DV-Hop-based model using a modified optimal anchor node sub-set (MOANS DV-Hop) is developed. A plan for AN utilization was projected. An objective function has been expressed to diminish the fault in assessing the organizes of unknown nodes. Every anchor node initially utilizes other ANs to discover itself and then utilizes the SGLEO technique. The AN then upgrades its average hop dimension utilizing the anchor node sub-set and shows both the upgrade size of the hop and the AN sub-set to the adjacent unknown nodes. Then it defines its position utilizing the EO system. Soundararajan et al. [12] developed a meta-heuristic optimizer-based NL and multi-hop routing protocol with mobile sink (MONL-MRPMS) for WSN. This system contains an effectual COA for NL in WSN, which aids in defining the position of the nodes repeatedly. Also, the seagull optimizer-based Multi-hop routing (SGO-MHR) procedure is intended for the optimal range of paths for inter-cluster transmission. Finally, a mobile sink (MS) with a route alteration system was used for enhanced energy efficacy of WSN. Gantassi et al. [13] proposed a novel IR-DV-Hop localization model. Especially, the developed mobile data collector-improved recursive distance vector-hop (MDC-IR-DV-Hop) protocol utilizes the MDC as a transitional among the CH and BS to improve QoS, decrease delays at the time of gathering data, and increase the transmission stage of the routing procedure.

Amutha et al. [14] concentrate on dual techniques such as Hybrid Butterfly and AC along with Static sink node (HBACS) and HBAC beside with MS node (HBACM). Also, in this paper, the flexibility of the sink node is employed to remove the multi-hop communication among sink nodes and cluster heads (CHs), therefore directing the hot-spot problem and spreading the network lifetime. In [15], a sink mobility-based energy-optimized routing (SMEOR) technique is projected in EH-enabled WSNs. While resulting in the routing of cluster-based, the selection of CH was implemented utilizing our projected ESHLFO model. Moreover, safety in SMEOR is certified by encoding the data utilizing a stream cipher and producing a security key.

Gupta et al. [16] projected an Energy Efficient Data Communication (EEDC) system by using RHCER—a multi-tier structure for energy routing decisions. The sensors used for IoT application data gathering obtain significant data and pick CHs depending upon a multi-criteria decision function. Moreover, to certify effective longer-distance communication besides load dispersal through every network node, a sub-model was utilized at every level of the projected structure. In [17], an effectual anchor-free localization structure for WSN named the CRSSA localization method is introduced. This method utilized the received signal strength (RSS) value and the context network connectivity in an anchor-free WSN. The technique presents and carefully analyses a new joint valuation technique. The technique then conveys diagnostic expressions for the key parameter, the node's communication array, and the value of PLE.

3. The Proposed Method

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In this study, we have developed an efficient SNPE-HHO algorithm in WSN. The main intention of the SNPE-HHO technique is to recognize the optimal position of the sink node in the network. Fig. 1 presents the entire procedure of the SNPE-HHO algorithm.

A. Network Assumptions

1. Every SN has the same patterns of energy and the utilized formation of transceivers [18].
2. Utilizing the digital magnetic range, the SN radiation and configuration pattern are exactly coordinated to the south and north poles.
3. Localized SNs always produce beacons with the highest transmission power over a definite period.
4. Afterward receiving a control packet from the AN, the unlocalized node itself switches the transceiver unit by 60°.
5. The swapped beam antennas are coordinated over time in the transceiver unit.
6. Every node recognizes its direction and velocity of a drive. In the projected method, the minimum amount of SNs ($\xi_{\min}$) is defined by the percentage of the entire targeted sensing area to the coverage area of every SN (hexagonal area).

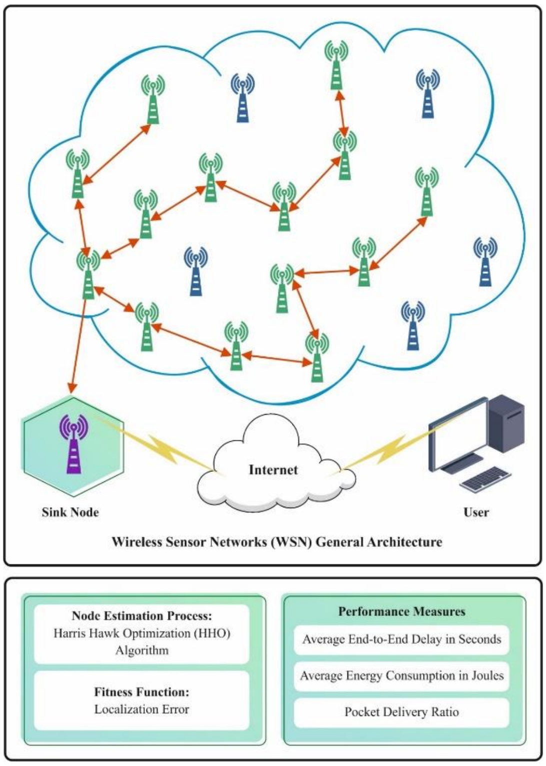

Figure 1: Overall process of SNPE-HHO algorithm

B. Design of HHO algorithm

The SNPE-HHO technique employs the HHO technique which appeals to motivation from the hunting tactics of Harris Hawk [19]. This bird perches in the air, scouts out a target from the distance, and jumps down on it in the show. The best solution is known as prey), whereas the candidate solution is known as Hawk (x).

Prior research shows that HHO is a robust optimization algorithm to more rapidly identify the best solution for the complex problem with less computation. The advantages of HHO include preventing local optima and shows the smooth passage from exploitation to exploration.

Using an optimizer algorithm, a problem space was widely explored to define the optimal solution. The metaheuristic begins the hunting during the exploration stage to discover the fittest location in the center of valleys and hills within the searching area.

$$h_{n+1}\begin{cases} h_{rand}(n)-a1|h_{rand}(n)-2a2h(n)| & l\geq 0.5 \\ h_{robbit}(n)-h_m(n)-a3\big(L+a4(U-L)\big) & l<0.5 \end{cases} \tag{1}$$

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In Eq. (1), h_{n+1} represents the location vector of Hawk, and $h_{rand}(n)$ implies the position vector of Hawk. $h(n)$ is the current location vector of Hawks, and $h_{rabbit}(n)$ denotes the optimum position. L and U are the lower and upper boundaries of variables, correspondingly. The variables $a1, a2, a3, a4$ are random numbers within [0,1]. The formula for $h_m(n)$, representing the mean location of N solution:

$$h_m(n) = \frac{1}{K}\sum_{t=1}^{N} h_t\,(n) \tag{2}$$

In Eq. (2), $h_t(n)$ inferred the hawk's location after n iteration and K indicates the overall hawk count.

During the escaping stage, the prey power (Z) considerably reduces, which causes the model to shift from exploration to exploitation.

$$Z = 2Z_0\left(1 - \frac{1}{T}\right) \tag{3}$$

In Eq. (3), the escaping energy is signified as Z, the iteration count is denoted by T, and the initial energy that differs from $[-1,1]$ at all the iterations is indicated as Z_0. Fig. 2 defines the steps involved in HHO.

Figure 2: Steps involved in HHO

The exploitation stage has four dissimilar strategies that are given in the following:

When $a \geq 0.5$ and $|Z| \geq 0.5$, the soft besiege is takes place. The Hawk modifies its place using the following equation:

$$h(n+1) = Dh(n) - Z|Jh_{rabbit}(n) - h(n)| \tag{4}$$

$$Dh(n) = h_{rabbit}(n) - h(n) \tag{5}$$

Where $J = 2(1 - a5)$ represents the jump power of the rabbits and the space between the rabbit and Hawk in iteration n is denoted as $Dh(n)$. Here, the random parameter is $r5$.

When $a \geq 0.5$ and $|Z| < 0.5$then hard besiege strategy occurs. The Hawk updated its position as:

$$h(n+1) = h_{robbit}(n) - Z|\triangle\, h(n)| \tag{6}$$

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When $|Z|ge0.5$ and $a0.5$ both exist, so a soft besiege approach with progressive quick dives is still advantageous. Every individual hawk chooses the finest location to objective the prey before the prey escapes at this phase as follows:

$$A = h_{robbit}(n) - Z|Jh_{rabbit}(n) - h(n)| \tag{7}$$

If the drive doesn't support the prey fighting, a dive is selected depending upon a levy flight (FL) that is expressed by:

$$M = A + S \times FL(E) \tag{8}$$

In Eq. (8), E denotes the dimension of the problem. S indicates the vector of a randomly generated number with a 1×D size. The FL function is formulated as:

$$FL(x) = 0.01 \times \frac{m \times \omega}{|n|^{\frac{1}{\delta}}}, \omega = \left(\frac{\tau(1-\delta) \times \sin\left(\frac{\pi\delta}{2}\right)}{\tau\left(\frac{1-\delta}{2}\right) \times \delta \times 2\left(\frac{1-\delta}{2}\right)} \right)^{\frac{1}{\delta}} \tag{9}$$

In Eq. (9), the delta is a constant with a value of 1.5, and m and n are randomly produced parameters within [0,1]. The following formula describes how Hawk's position is updated by the soft besiege stage:

$$h_{n+1} \begin{cases} A & if\ E(A) < E\big(h(n)\big) \\ M & if\ E(M) < E\big(h(n)\big) \end{cases} \tag{10}$$

In Eq. (10), A and M are attained by Eqs. (7) & (8), and both represent the next location of the new iteration.

When $|Z| < 0.5$ and $a < 0$, then besiege with progressive quick dives takes place as:

$$h_{n+1} \begin{cases} A' & if\ E(A') < E\big(h(n)\big) \\ M' & if\ E(M,) < E\big(h(n)\big) \end{cases} \tag{11}$$

$$A' = h_{rabbit}(n) - Z|Jh_{rabbit}(n) - h(n)| \tag{12}$$

$$M' = A' + S \times FL(D) \tag{13}$$

Where $h_m(n)$ is attained using Eq. (2).

C. Sink Node Estimation Process

Next, the SNPE-HHO technique computes a fitness function (FF) that can lead the searching path of the HHO algorithm and enhance the node estimation performance. In RSSI-based localization models, the location of UNs is projected from the usual signal strength [20]. The trilateral localization system is a normally utilized node localization model that executes the basic standard of localization such as 3 ANs being positioned as $P_1(x_1, y_1)$, $P_2(x_2, y_2)$, and $P_3(x_3, y_3)$. When there presents an unknown node positioned as $Q(x, y)$ and their distances as d_1, d_2, and d_3. The 3 ANs and the consistent communication range were employed as the radius and center to appeal to the 3 circles correspondingly, and their one and only point of connection is the unknown node location.

From the standard of the traditional trilateral localization model, it is recognized that the smallest 3 ANs are wanted to attain the localization of the UN. An appropriate and precise FF can direct the hunt path of the SNPE-HHO and enhance the efficacy of performance. The FF is expressed as below:

$$F(x, y) = \frac{1}{m} \sum_{i=1}^{m} \left(\sqrt{(x - x_i)^2 + (y - y_i)^2} - \hat{d}_i \right)^2 \tag{14}$$

Whereas, m denotes the amount of ANs and $m \geq 3$. (x, y) represents the position of UNs, $(\chi_{i,} y_i)$ refers to the position of the ith AN, and $\hat{d}_i$ indicates the distance estimation of AN and UN. The error among the UNs and the forecast location is a significant pointer of the localization solution of the system. To certify the ability of complete error of localization, we assume the mean value of k as the concluding error. The error calculation is given below:

$$Err = \frac{1}{k} \sum_{i=1}^{k} sqrt\left((x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2\right) \tag{15}$$

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Whereas, k denotes the amount of UNs, (x_i, y_i) represents the definite position of the ith unknown node, and $(\hat{x}_i, \hat{y}_i)$ refers to the assessed position of the ith node.

4. Result Analysis and Discussion

In this part, the performance analysis of the SNPE-HHO technique is given. In Table 1 and Fig. 3, the average end to end delay (AETED) results of the SNPE-HHO technique is equated with other models [18]. The outcomes specify the supremacy of the SNPE-HHO technique with the least AETED values. With a speed of 10m/s, the SNPE-HHO technique offers lower AETED of 0.025s whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AETED of 0.030s, 0.082s, 0.083s, and 0.101s, correspondingly. Moreover, With the speed of 20m/s, the SNPE-HHO model provides a lesser AETED of 0.026s whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AETED of 0.032s, 0.082s, 0.084s, and 0.097, correspondingly. Furthermore, With a speed of 30m/s, the SNPE-HHO technique offers a lower AETED of 0.027s while the RDCM, VELCT, MBC, and ESWCA systems attain greater AETED of 0.032s, 0.084s, 0.086s, and 0.095s, correspondingly.

Table 1: AETED analysis of SNPE-HHO technique with other models under various speed

Average end-to-end delay in seconds (s)					
Speed in (m/s)	SNPE-HHO	RDCM	VELCT	MBC	ESWCA
10	0.025	0.030	0.082	0.083	0.101
20	0.026	0.032	0.082	0.084	0.097
30	0.027	0.032	0.084	0.086	0.095
40	0.027	0.034	0.084	0.088	0.096
50	0.028	0.033	0.086	0.088	0.095

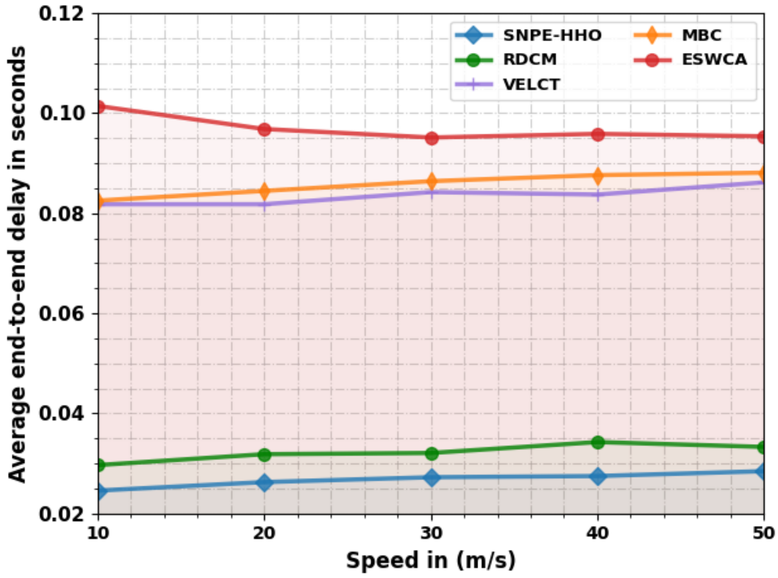

Figure 3: AETED analysis of SNPE-HHO technique under various speed

In Table 2 and Fig. 4, the average energy consumption (AECON) in joules outcomes of the SNPE-HHO model is compared with other methods. The outcomes state the supremacy of the SNPE-HHO approach with the smallest AECON values. With the speed of 10m/s, the SNPE-HHO technique offers a lower AECON of 2.049J whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AECON of 2.090J, 2.293J, 2.381J, and 2.440J, correspondingly.

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Table 2: AECON analysis of SNPE-HHO technique with other models under various speed

Average energy consumption in joules (J)					
Speed in (m/s)	SNPE-HHO	RDCM	VELCT	MBC	ESWCA
10	2.049	2.090	2.293	2.381	2.440
20	2.116	2.170	2.379	2.526	2.689
30	2.139	2.210	2.436	2.608	2.743
40	2.165	2.246	2.535	2.632	2.784
50	2.203	2.265	2.618	2.687	2.796

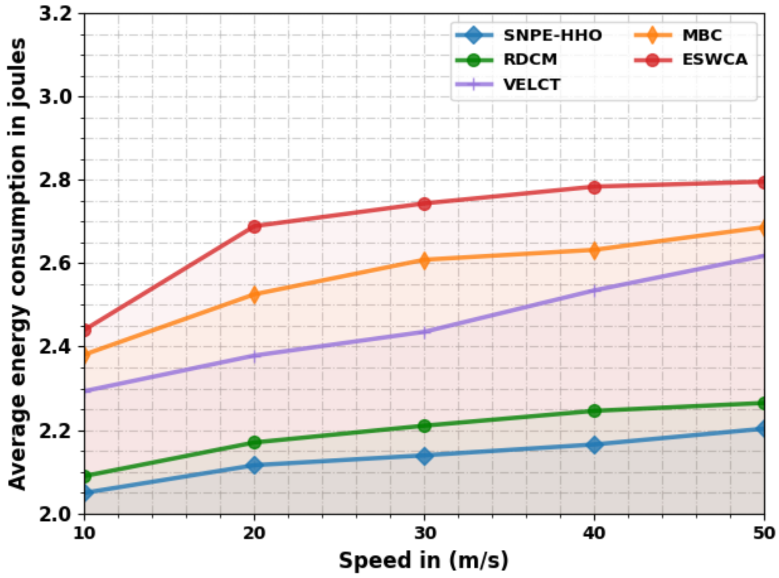

Figure 4: AECON analysis of SNPE-HHO technique under various speed

Furthermore, With the speed of 20m/s, the SNPE-HHO technique offers a lower AECON of 2.116J whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AECON of 2.170J, 2.379J, 2.526J, and 2.689J, correspondingly. Likewise, With the speed of 30m/s, the SNPE-HHO technique offers a lower AECON of 2.139J whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AECON of 2.210J, 2.436J, 2.608J, and 2.743J, correspondingly.

The comparative packet delivery ratio (PDR) results of the SNPE-HHO technique are reported in Table 3 and Fig. 5. The outcomes emphasized that the ESWCA system has shown ineffectual performance over other approaches. In addition, the MBC model has obtained slightly increased PDR values. Although the RDCM and VELCT models have resulted in closer PDR values, the SNPE-HHO technique highlighted improved PDR values of 99.39%, 98.10%, 97.41%, 96.19%, and 95.10% under the speed limit of 10-50m/s, correspondingly.

Table 3: PDR analysis of SNPE-HHO technique with other models under various speed

Packet delivery ratio (%)					
Speed in (m/s)	SNPE-HHO	RDCM	VELCT	MBC	ESWCA
10	99.39	98.23	91.49	89.11	79.91
20	98.10	96.80	89.38	87.61	79.98
30	97.41	95.51	87.74	87.13	79.23
40	96.19	94.42	87.13	85.22	78.69

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50	95.10	91.42	86.52	84.07	76.98

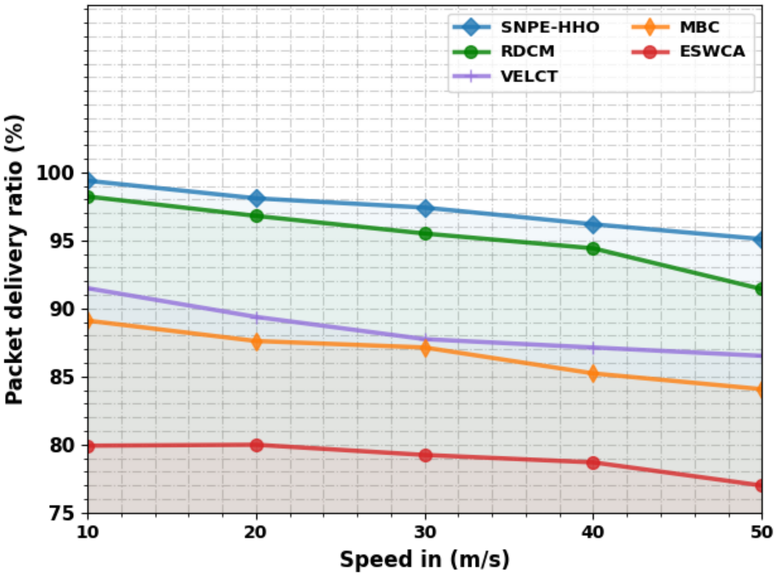

Figure 5: PDR analysis of SNPE-HHO technique under various speed

In Table 4 and Fig. 6, the AECON in joules results of the SNPE-HHO model are compared with other methods. The outcomes state the supremacy of the SNPE-HHO technique with the smallest AECON values.

Table 4: AECON analysis of SNPE-HHO technique with other models under various no. of nodes

Average energy consumption in joules (J)					
Number of nodes	SNPE-HHO	RDCM	VELCT	MBC	ESWCA
100	1.315	1.348	1.418	1.506	1.682
200	1.342	1.372	1.519	1.593	1.693
300	1.411	1.441	1.611	1.633	1.704
400	1.447	1.519	1.660	1.689	1.725
500	1.481	1.535	1.686	1.737	1.743

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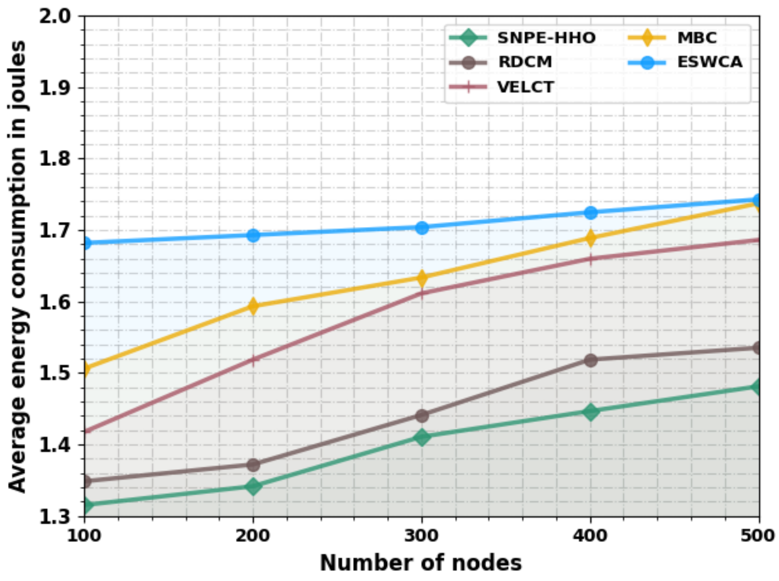

Figure 6: AECON analysis of SNPE-HHO technique under various no. of nodes

With 100 nodes, the SNPE-HHO technique offers a lower AECON of 1.315J whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AECON of 1.348J, 1.418J, 1.506J, and 1.682J, correspondingly. Also, With 200 nodes, the SNPE-HHO system provides a lower AECON of 1.342J whereas the RDCM, VELCT, MBC, and ESWCA techniques obtain higher AECON of 1.372J, 1.519J, 1.593J, and 1.693J, correspondingly. Likewise, With 300 nodes, the SNPE-HHO technique offers a lower AECON of 1.411J whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AECON of 1.441J, 1.611J, 1.633J, and 1.704J, respectively.

In Table 5 and Fig. 7, the AETED outcomes of the SNPE-HHO technique are equated with other methods. The outcomes specify the supremacy of the SNPE-HHO technique with the least AETED values.

Table 5: AETED analysis of SNPE-HHO technique with other models under various no. of nodes

Average end-to-end delay in seconds (s)					
No. of nodes	SNPE-HHO	RDCM	VELCT	MBC	ESWCA
100	0.026	0.029	0.084	0.087	0.097
200	0.027	0.031	0.084	0.088	0.098
300	0.028	0.032	0.083	0.087	0.099
400	0.027	0.031	0.084	0.087	0.099
500	0.026	0.030	0.086	0.089	0.102

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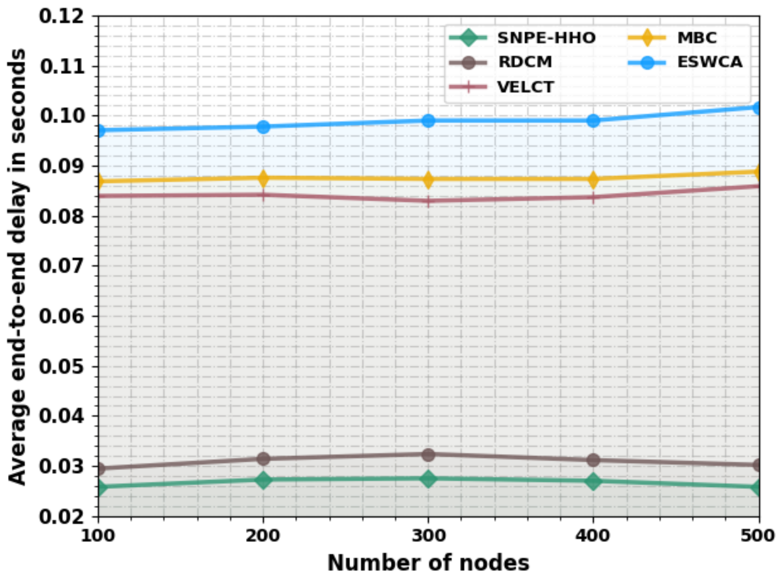

Figure 7: AETED analysis of SNPE-HHO technique under various no. of nodes

With 100 nodes, the SNPE-HHO technique offers a lower AETED of 0.026s whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AETED of 0.029s, 0.084s, 0.087s, and 0.097s, correspondingly. Moreover, With 200 nodes, the SNPE-HHO model provides a lesser AETED of 0.027s whereas the RDCM, VELCT, MBC, and ESWCA models obtain higher AETED of 0.031s, 0.084s, 0.088s, and 0.098s, correspondingly. Furthermore, With 300 nodes, the SNPE-HHO system gets a lesser AETED of 0.028s while the RDCM, VELCT, MBC, and ESWCA systems attain greater AETED of 0.032s, 0.083s, 0.087s, and 0.099s, correspondingly.

Table 6: PDR analysis of SNPE-HHO technique with other models under various no. of nodes

Pocket delivery ratio (%)					
Number of nodes	SNPE-HHO	RDCM	VELCT	MBC	ESWCA
100	99.15	98.16	92.29	91.57	81.94
200	98.75	97.63	90.97	90.25	81.48
300	98.42	97.30	90.25	89.13	81.81
400	98.23	97.10	89.52	87.94	80.03
500	97.83	97.04	89.19	87.15	79.10

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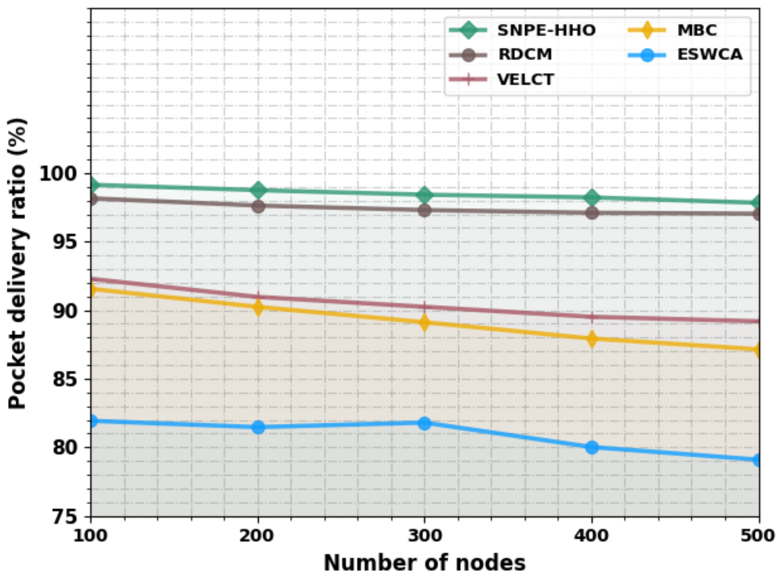

Figure 8: PDR analysis of SNPE-HHO technique under various no. of nodes

The comparative PDR outcomes of the SNPE-HHO system are reported in Table 6 and Fig. 8. The results emphasized that the ESWCA system has shown ineffectual performance over other techniques. Furthermore, the MBC method has slightly enlarged PDR values. Although the RDCM and VELCT systems have resulted in closer PDR values, the SNPE-HHO approach highlighted enhanced PDR values of 99.15%, 98.75%, 98.42%, 98.23%, and 97.83% under nodes of 100-500, correspondingly.

5. Conclusion

In this study, we have developed an efficient SNPE-HHO algorithm in WSN. The main intention of the SNPE-HHO technique is to recognize the optimal position of the sink node in the system. To complete this, the SNPE-HHO approach uses the HHO system that appeals to motivation from the hunting tactics of Harris Hawk. Moreover, the SNPE-HHO technique computes an FF that can lead the searching direction of the HHO algorithm and enhance the node estimation performance. The performance study of the SNPE-HHO system is verified utilizing distinct metrics. The experimentation values confirmed the improved estimation performance of the SNPE-HHO technique over other existing approaches

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