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Original scientific paper

Hybrid Sine-Cosine Black Widow Spider Optimization based Route Selection Protocol for Multihop Communication in IoT Assisted WSN

S. BALAKRISHNAN, K. VINOTH KUMAR*

Abstract: In the modern era, Internet of Things (IoT) has been a popular research topic and it focuses on interconnecting numerous sensor-based devices primarily for tracking applications and collecting data. Wireless Sensor Networks (WSN) becomes a significant element in IoT platforms since its inception and turns out to be the most ideal platform for deploying various smart city application zones namely disaster management, home automation, intelligent transportation, smart buildings, and other IoT-enabled applications. Clustering techniques were commonly used energy-efficient methods with the main purpose that is to balance the energy between Sensor Nodes (SN). Routing and clustering are Non-Polynomial (NP) hard issues where bio-inspired approaches were used for a known time to solve these issues. This study introduces a Hybrid Sine-Cosine Black Widow Spider Optimization based Route Selection Protocol (HSBWSO-RSP) for Mulithop Communication in IoT assisted WSN. The presented HSBWSO-RSP technique aims to properly determine the routes to destination for multihop communication. Moreover, the HSBWSO-RSP approach enables the integration of variance perturbation mechanism into the traditional BWSO algorithm. Furthermore, the selection of routes takes place by a fitness function comprising Residual Energy (*RE*) and distance (*DIST*). The experimental result analysis of the HSBWSO-RSP technique is tested using a series of experimentations and the results are studied under different measures. The proposed methodology achieves 100% packet delivery ratio, no packet loss and 2.33 secs end to end delay. The comparison study revealed the betterment of the HSBWSO-RSP technique over existing routing techniques.

Keywords: fitness function; Internet of Things; metaheuristics; route selection; sine cosine algorithm; wireless sensor networks

1 INTRODUCTION

The Internet of Things (IoT) is an extensive and accessible network of sensors linked to the Internet enabling the capability for transferring and auto-organizing data on a network with minimal intervention of humans [1]. It is an intellectual network that acts and reacts in face of circumstances and changes in the platform. With the advancement of transmission technology involving radio frequency identification and wireless sensor networks (WSNs), IoT offers immediate access to data of all devices, ensuring great efficiency and productivity [2]. IoT enables things and people for communicating anywhere, anytime, with anyone and anything utilizing any service and network, depending on WSN technologies [3].

Due to the flexibility and manageability of configuration, WSNs were critical elements of IoT systems. The WSN sensed the dataset and transferred it to base station (BS) by wireless transmission through some of the cluster heads (*CH*s) and gateway [4]. *CH*s are responsible for collecting data packets and transmitting them to the BS. *CH*s act as main hub for transmitting data over multi-hop or single hop networks. Additionally, *CH*s retain obtained data packets in memory and followed store and forward system [5].

Routing protocols are a vital factor in the fundamental technologies that support WSNs [6]. In this technique, the energy of nodes is often lost in system that is accountable for data connection, and overall energy utilization of nodes is inconsistent. Thus, the critical part of routing method was reducing and balancing power that can be used by the network [7]. The existing routing protocols for WSN-based IoT are divided into 3 types' location, flat, and hierarchical-oriented protocols. Every sensor device in flat-type routing protocols executes an equal role in obtaining data from the atmosphere and sending it to the IoT hub [8]. The distance among devices can be calculated on the basis of the received signal strength in location-related routing protocols. This data can be leveraged for effective data transfer. Hierarchical routing protocol is the commonly employed routing protocol for WSN-based IoT networks. It divides entire network area into various zones [9]. Every partition includes many member nodes and a master node. The master node was accountable to collect data from member nodes and sending it to the hub. Furthermore, it can efficiently balance load on sensor devices by allotting different tasks to various gadgets [10]. Hierarchical routing can be a viable choice to reduce energy utilization by removing redundant data transmission. Owing to its high energy-efficiency, it surpasses other kinds of routing protocols.

In [11], the authors introduced a cluster-related multihop routing technique. In this presented technique, integration of 2 methods called K-means and Open-Source Development Model Algorithm (ODMA), were used for GA and can be implemented for multihop routing. Rajaram and Kumaratharan [12] devised a technique related to a three tier multi-hop optimized routing technique (TM-ORT) and fuzzy and unequal clustering (FBUCA) for enhancing the network performance. Data reliability and Energy consumption were stabilized by QOS related multihop routing protocols. When clustering acts a key role, LB among the clusters is significant to concentrate. LB was attained by selecting optimal parameters for fuzzy related clustering for choosing an effective *CH* for routing and data aggregation.

Kavitha et al. [13] devised a cryptographic related clustering framework to preserve data privacy utilizing Optimal Privacy-Multihop Dynamic Clustering Routing Protocol (OP-MDCRP) that scale up energy efficient routing and data privacy for heterogeneous networks which leverages multi-hop communication and clustering for minimizing energy usage of SN and expands lifespan of WSN. This technique even offers high data privacy utilizing ECIES-KPM abbreviated as Elliptic Curve Integrated Encryption-Key Provisioning Method with small sized key. In [14], a CS-related method was modelled for transferring the data effectively via WSNs, which employs Multiple Objectives GA (MOGA) for maximizing the sensing matrix, count of measurements, and transmission range. The method intends at striking right balance among accuracy and energy efficiency. It builds path in a multihop manner that relies upon enhanced values.

Daniel et al. [15] presented the new EAANFC-MR abbreviated as Energy Aware Adaptive Fuzzy neuro clustering with WSN based IoT method. EAANFC-MR was modelled for two main phases, multihop routing, and clustering based on EAANFCs. The EAANFC related cluster method was utilized for choosing *CH*s with *RE* and Distance and Node degrees. The QOBFO method, which can be used as a Multihop Route approach, was used for choosing optimized roads to destiny. Muthukkumar et al. [16] devise a GA-related energy-aware multihop clustering (GA-EMC) method for heterogeneous WSN (HWSN). In HWSNs, every node has to change initial energy and naturally has a restriction on energy consumption. A GA determines the best *CH*s and network positions. The fitness of chromosomes can be computed in terms of the node's residual energy, distance, and optimal *CH*s. Multi-hop transmission enhances energy efficiency in HWSNs.

This study introduces a Hybrid Sine-Cosine Black Widow Spider Optimization based Route Selection Protocol (HSBWSO-RSP) for Multihop Communication in IoT assisted WSN. The presented HSBWSO-RSP technique aims to properly determine the routes to destination for multihop communication. Moreover, the HSBWSO-RSP technique enables the integration of variance perturbation mechanism into the traditional BWSO algorithm. Furthermore, the selection of routes takes place by a fitness function encompassing residual energy (*RE*) and distance (*DIST*). The experimental result analysis of the HSBWSO-RSP technique is tested using a sequence of experimentations and results are studied under different measures. The comparison study revealed the betterment of the HSBWSO-RSP approach over existing routing techniques.

This paper is organized in the following way: section 2 discusses the proposed research model, which includes design of proposed algorithm, and section 3 offers results and discussion and finally section 4 offers conclusion with future findings.

2 THE PROPOSED MODEL

In this study, we have introduced a novel HSBWSO-RSP for mulithop communication in IoT based WSN. The presented HSBWSO-RSP method aims to properly determine the routes to destination for multihop communication. Furthermore, the selection of routes takes place by a fitness function comprising *RE* and distance *DIST*. Fig. 1 represents the overall procedure of HSBWSO-RSP system.

2.1 System Model

WSN has many SN and BS. The subsequent property can be assumed as sensor network.

- All the nodes are heterogeneous. The nodes can be randomly assigned with sensor domain.
- The node has unique ID and it cannot transfer then being employed.
- BS which lies outside network.
- The BS is a constant power supply and it takes no energy constraint.
- BS and Node can be static and assumed as inactive.
- The transmission between SN occurs using multihop symmetric transmission.
- SNs were linked with GPS devices and Locations aware.

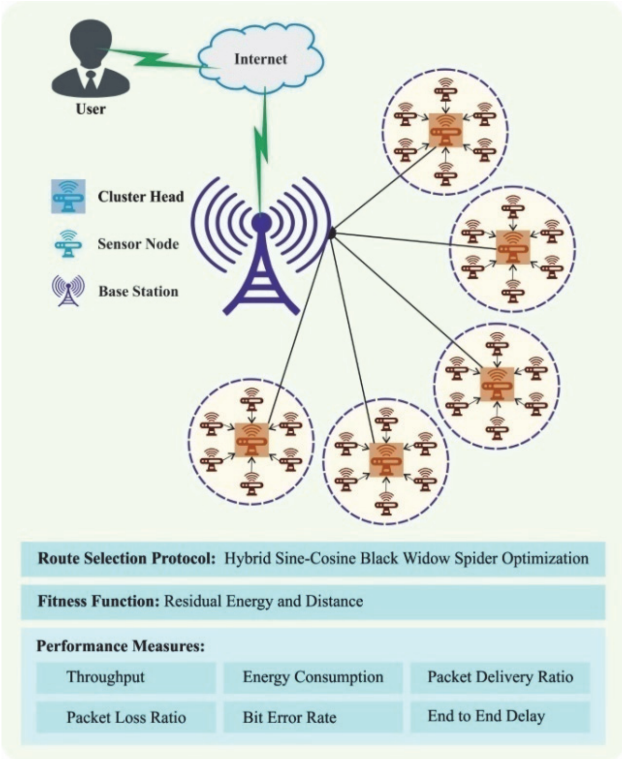

Figure 1 Overall procedure of HSBWSO-RSP approach

2.2 Design of HSBWSO Algorithm

In this work, the HSBWSO-RSP technique enables the integration of variance perturbation mechanism into the traditional BWSO algorithm. This section presents a courtship-mating movement strategy and mathematical modeling of pheromone rate in black widow spiders [17]. The BW spider moves within the spider web in a spiral and linear manner and it can be mathematically expressed in the following equations:

$$\vec{x}_i\left(t+1\right)\vec{x}_*\left(t\right)-m\vec{x}_{r1}\left(t\right) \quad (1)$$

$$\vec{x}_i\left(t+1\right)\vec{x}_*\left(t\right)-\cos\left(2\pi\beta\right)\vec{x}_i\left(t\right) \quad (2)$$

where $\vec{x}_i\left(t+1\right)$ represents the individual location after the update and $\vec{x}_*\left(t\right)$ shows the present optimum individual location.

Random number is directly or indirectly generated by the rand function (generate random number within [0, 1]). m stands for the random floating-point number in [0.4, 0.9]. β means a random integer within [−1, 1]. r_1 shows a random number between 1 and the maximal population size. $\vec{x}_{r1}\left(t\right)$ denotes the selected random location r_1 and

$\vec{x}_i(t)$ indicates the present individual location. The way BW spider moves can be defined by random numbers. Once the random number produced by the rand function is lesser than or equivalent to 0.3, Eq. (1) is selected for individual movement mode, or else, Eq. (2) is selected. Sex pheromone serves a vital role in the courtship method of BW spider. A well-nourished female spider produces more silk than starving female. Male spider is more responsive to sex pheromone from well-nourished female spider since they offer a high level of fertility such that male spider mainly avoids cost of risking mating with hungry female spider. Thus, male spiders do not select females with lower sex pheromone levels. This can be equated in the following equation:

$$pheromene(i)=\frac{fitness_{\max}-fitness(i)}{fitness_{\max}-fitness_{\min}} \tag{3}$$

In Eq. (3), $fitness_{\max}$ and $fitness_{\min}$ characterize the worst and best fitness value in the present population, $fitness(i)$ represent the fitness value of the i-th individual. The sex pheromone vectors contain normalized fitness within [0, 1]. For individuals with sex pheromone rates lesser than or equivalent to 0.3, the location updating model is expressed by using Eq. (4). Fig. 2 demonstrates the steps involved in BWSO.

$$\vec{x}_i(t)=\vec{x}_*(t)+\frac{1}{2}\left[\vec{x}_{r1}(t)-(-1)^{\sigma}\vec{x}_{r2}(t)\right] \tag{4}$$

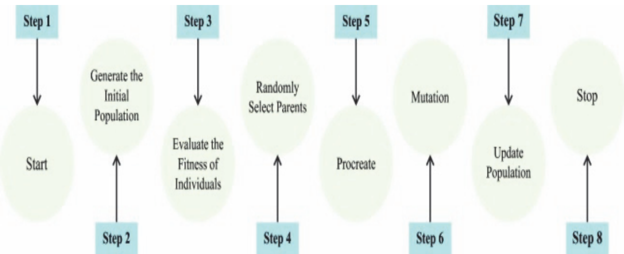

Figure 2 Steps involved in BWSO

Now, $\vec{x}_i(t)$ shows the location of female BW spiders with lower sex pheromone levels. r_1 and r_2 denote the random integer from 1 to the maximal population size, and $r_1 \neq r_2$. σ indicates the random integer ranges from zero to one. Mirjalili [18] proposed a sine cosine algorithm (SCA) that is a nature-inspired optimization technique. The algorithm produces more than one random candidate solution. The mathematical properties of the sine and cosine functions are used for adaptively changing the amplitude of both functions. Sequentially, the algorithm balances local exploitation globally, and exploration abilities in the search agent and lastly finds the best global solution:

$$\vec{x}_i(t+1)=\vec{x}(t)+l_1\cdot\sin l_2\cdot\left|l_3\cdot\vec{x}_*(t)\rightarrow-\vec{x}(t)\right| \tag{5}$$

$$\vec{x}_i(t+1)=\vec{x}(t)+l_1\cdot\cos l_2\cdot\left|l_3\cdot x_*(t)-\vec{x}(t)\right| \tag{6}$$

From the above equations, $\vec{x}(t+1)$ indicates the individual location after updating. $\vec{x}_*$ denotes the present optimum individual location. l_2 represent the random integer ranges from 0 to 2π and l_3 denotes the random number within the interval of [0, 2]. $\overrightarrow{\chi_i}(t)$ indicates the present individual location. l_4 represents random integer within [0, 1]. If $l_4 < 0.5$, the location updating can be implemented by means of Eq. (8), or else, the location is upgraded by means of Eq. (7). l_1 can be defined as follows:

$$l_1=a\cdot\left(1-\frac{t}{T}\right) \tag{7}$$

In Eq. (8), a indicates the constant that usually takes the value of 2. t denotes the number of existing iterations, and T signifies the maximal amount of iterations. The random integer was produced by the rand function to be lesser than or equivalent to the p mutation probability for performing the mutation and this can be formulated as follows:

$$p=\exp\left(1-\frac{t}{T}\right)^{-20}+0.35 \tag{8}$$

Assume that the maximal amount of iterations T is 500, and hence the variation trend of the mutation probability has been given in the following: The introduction of p mutation probability controls the weight for performing mutation. The probability of performing mutation function is high in the middle and earlier stages. The probability of performing mutation in the later part of the model is zero or even small. The SCA is developed as a variance perturbation approach to the original BWSO algorithm and is represented as SBWSO algorithm.

2.3 Application of HSBWSO Algorithm for Route Selection Process

During this phase, the available paths between BS as well as CH nodes can be introduced as an initial population to optimize the technique. Primarily, most CH can deliberate as transmitters and other CHs can be considered as in-between sinks or paths. Therefore, during this initialized phase, all the potential paths between CH as well as sink are formulated in Eq. (9).

$$Sol=P_i,\ i=1,\ 2,\ ...,\ N \tag{9}$$

In which, 'Sol' implies initial population set, P_i signifies i-th paths between sink as well as CH, 'N' defines the entire count of paths. The paths contain entire energy and distance.

$$P=\{RE, DIST\} \tag{10}$$

Assume 'RE' refers to residual energy (RE) of nodes from path, 'DIST' signifies overall distance of paths. The SD for RE (σ_{RE}) was utilized for measuring quality of uniform load distribution between sensors as follows Eq. (10).

$$RE = f_1 = \sigma_{RE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left\{\mu_{RE} - e\left(node_j\right)\right\}^2} \quad (11)$$

At this point, $\mu_{RE} = \frac{1}{n}\sum_{i=1}^{n} E\left(node_j\right)$.

Whereas, 'n' signifies the entire count of nodes that are presented from the path and '$E\left(node_j\right)$' defines the RE of the i-th node from path. Afterward, distance between transmitter CH to sink calculated by count of Euclidean distance between all the CHs from the path is formulated as Eq. (12).

$$DIST = \\ = \sum_{i}^{n-1}\sqrt{\left(CH_i\left(x\right) - CH_{i+1}\left(x\right)\right) + \left(CH_i\left(y\right) - CH_{i+1}\left(y\right)\right)} \quad (12)$$

In which, '$CH_i\left(x\right)$' and '$CH_i\left(y\right)$' portray x & y coordinate of i-th CH from the path correspondingly. So, the primary goal of projected optimizing is energy reduction. The next objective was to reduce path distance which is written in Eq. (12). Thus, such 2 variables of all the paths can be introduced as an initial population.

During this phase, the fitness of all the solutions or paths between sink as well as CH is calculated. The key objective of optimizing was to realize path has short distance and minimal power consumption. Thus, the main function contains distance of all the paths and energy. The FF was connected as minimalized function and it can be product of distances and energy which is demonstrated in Eq. (13).

$$F_i = \min\left\{RE_i \times DIST_i\right\} \quad (12)$$

where, 'F_i' stands for the fitness of i-th population, 'RE_i' implies the energy required from the i-th population and '$DIST_i$' signifies the entire distance of i-th population/path.

4 RESULTS AND DISCUSSION

In this section, the overall performance of the HSBWSO-RSP method is investigated in terms of different measures. Tab. 1 offers a comparative outcome of the HSBWSO-RSP method with recent models in terms of ECON, NLT, and THROP [19]. In Fig. 3, a comparison study of the HSBWSO-RSP model with other routing protocols in terms of ECON is given. The results indicated that the HEED technique has shown poor performance with maximum ECON values. Next, the FEEC-IIR, NE-EPO, and FRLDG techniques have reported moderately closer ECON values. Although the BiHCLR technique has reached reasonable ECON value, the HSBWSO-RSP model has exhibited better performance with reduced ECON values.

Table 1 Comparative analysis of HSBWSO-RSP system with other approaches under distinct nodes

No. of Nodes	HSBWSO-RSP	BiHCLR	FEEC-IIR	NF-EPO	FRLDG	HEED
Energy Consumption / mJ						
100	7	26	41	57	68	134
200	16	37	71	86	107	157
300	24	47	99	108	140	177
400	35	58	114	140	160	211
500	44	74	145	166	185	251
Network Lifetime (Rounds)						
100	5500	5500	5500	5000	4800	4290
200	5473	5340	5200	4780	4600	4000
300	5462	5350	5010	4690	4370	3830
400	5430	5220	4900	4320	4100	3410
500	5387	5230	4700	4090	3890	3090
Throughput / Mbps						
100	0.9963	0.9863	0.9481	0.9100	0.8035	0.7574
200	0.9802	0.9642	0.8236	0.7754	0.6931	0.7092
300	0.9770	0.9501	0.7333	0.6931	0.6027	0.6288
400	0.9642	0.9280	0.6650	0.5987	0.5405	0.5204
500	0.9575	0.9200	0.6308	0.5365	0.4521	0.4782

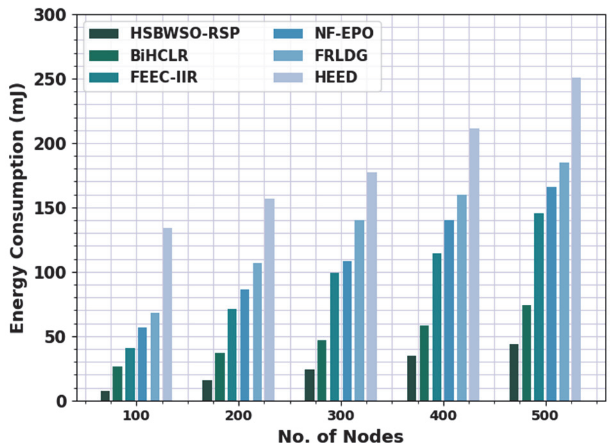

Figure 3 ECON analysis of HSBWSO-RSP system under distinct nodes

A detailed NLT investigation of the HSBWSO-RSP method with other existing models under various nodes is portrayed in Fig. 4. The obtained values signify the HSBWSO-RSP method has shown maximum NLT values. For instance, on 200 nodes, the HSBWSO-RSP model has gained improved NLT of 5473 rounds while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED models have reported reduced NLT of 5340, 5200, 4780, 4600, and 4000 rounds respectively. Also, on 300 nodes, the HSBWSO-RSP technique has obtained improved NLT of 5462 rounds while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED approaches have reported reduced NLT of 5350, 5010, 4690, 4370, and 3830 rounds correspondingly. Also, on 500 nodes, the HSBWSO-RSP technique has reached improved NLT of 5387 rounds while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED models have reported reduced NLT of 5230, 4700, 4090, 3890, and 3090 rounds correspondingly.

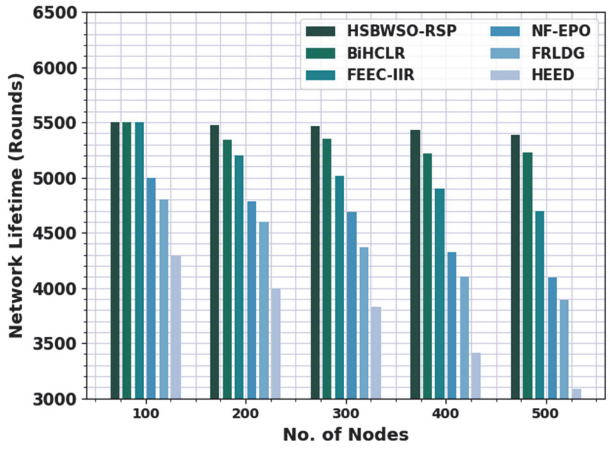

Figure 4 NLT analysis of HSBWSO-RSP system under distinct nodes

A brief THROP inspection of the HSBWSO-RSP approach with other existing techniques under various nodes is seen in Fig. 5. The gained values inferred that the HSBWSO-RSP approach has shown maximum THROP values. For example, on 200 nodes, the HSBWSO-RSP approach has achieved improved THROP of 0.9963 Mbps while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED methods have reported reduced THROP of 0.9863 Mbps, 0.9481 Mbps, 0.9100 Mbps, 0.8035 Mbps, and 0.7574 Mbps correspondingly.

Similarly, on 300 nodes, the HSBWSO-RSP technique has acquired improved THROP of 0.9970 Mbps rounds while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED approaches have reported reduced THROP of 0.9501 Mbps, 0.7333 Mbps, 0.6931 Mbps, 0.6027 Mbps, and 0.6288 Mbps correspondingly. Also, on 500 nodes, the HSBWSO-RSP method has gained improved THROP of 0.9575 Mbps while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED approaches have reported reduced THROP of 0.9200 Mbps, 0.6308 Mbps, 0.5365 Mbps, 0.4521 Mbps, and 0.4782 Mbps correspondingly.

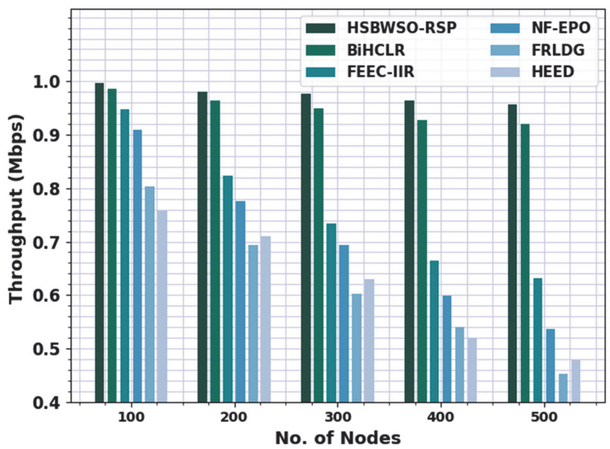

Figure 5 THROP analysis of HSBWSO-RSP system under distinct nodes

Tab. 2 offers a comparative outcome of the HSBWSO-RSP method with recent methods in terms of PDR, PLR, and ETED. The brief PDR inspection of the HSBWSO-RSP technique with other existing methods under various nodes is given in Fig. 6. The figure exhibits that the HSBWSO-RSP approach has shown maximum PDR values. For example, on 200 nodes, the HSBWSO-RSP model has gained improved PDR of 99.71% while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED approaches have reported reduced PDR of 98.96%, 98.04%, 97.12%, 96.04%, and 93.97% correspondingly.

Similarly, on 300 nodes, the HSBWSO-RSP method has reached improved PDR of 98.98% rounds while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED approaches have reported reduced PDR of 98.12%, 97.08%, 96.04%, 94.09%, and 92.05% correspondingly. Also, on 500 nodes, the HSBWSO-RSP method has attained improved PDR of 97.48% while the BiHCLR, FEEC-IIR, NF-EPO, FRLDG, and HEED models have reported reduced PDR of 96.08%, 94.97%, 94.09%, 92.05%, and 88.06% correspondingly.

Table 2 Comparative analysis of HSBWSO-RSP system with other approaches under distinct nodes

No. of Nodes	HSBWSO-RSP	BiHCLR	FEEC-IIR	NF-EPO	FRLDG	HEED
Packet Delivery Ratio / %						
100	100.00	100.00	99.08	98.08	97.04	95.08
200	99.71	98.96	98.04	97.12	96.04	93.97
300	98.98	98.12	97.08	96.04	94.09	92.05
400	97.98	96.93	96.08	95.08	93.09	89.98
500	97.48	96.08	94.97	94.09	92.05	88.06
100	100.00	100.00	99.08	98.08	97.04	95.08
Packet Loss Ratio / %						
100	0.00	0.00	0.92	1.92	2.96	4.92
200	0.29	1.04	1.96	2.88	3.96	6.03
300	1.02	1.88	2.92	3.96	5.91	7.95
400	2.02	3.07	3.92	4.92	6.91	10.02
500	2.52	3.92	5.03	5.91	7.95	11.94
End to End Delay / sec						
100	2.33	3.10	3.92	4.13	4.61	5.75
200	2.35	3.40	3.98	4.88	5.54	6.45
300	2.92	3.95	4.85	6.02	6.51	7.26
400	3.33	3.95	5.60	7.68	8.10	8.46
500	3.53	4.61	6.20	8.76	9.19	9.49

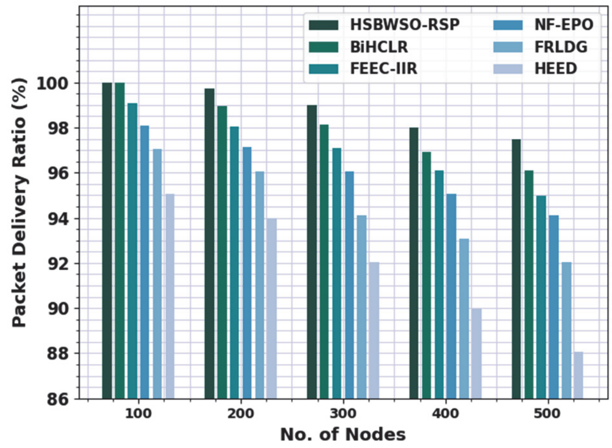

Figure 6 PDR analysis of HSBWSO-RSP system under distinct nodes

In Fig. 7, a comparative study of the HSBWSO-RSP method with other routing protocols in terms of PLR is given. The results indicate that the HEED method has shown poor performance with maximum PLR values. Next, the FEEC-IIR, NE-EPO, and FRLDG techniques have reported moderately closer PLR values. Although the BiHCLR approach has reached reasonable PLR value, the

HSBWSO-RSP model has shown better performance with reduced PLR values.

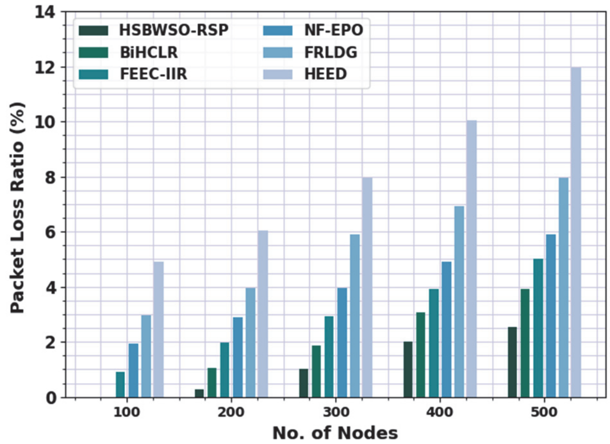

Figure 7 PLR analysis of HSBWSO-RSP system under distinct nodes

In Fig. 8, a comparative analysis of the HSBWSO-RSP method with other routing protocols in terms of ETED is given. The results specify the HEED approach has shown poor performance with maximum ETED values. Then, the FEEC-IIR, NE-EPO, and FRLDG methods report moderately closer ETED values. Although the BiHCLR algorithm has reached reasonable ETED value, the HSBWSO-RSP model has shown better performance with reduced ETED values.

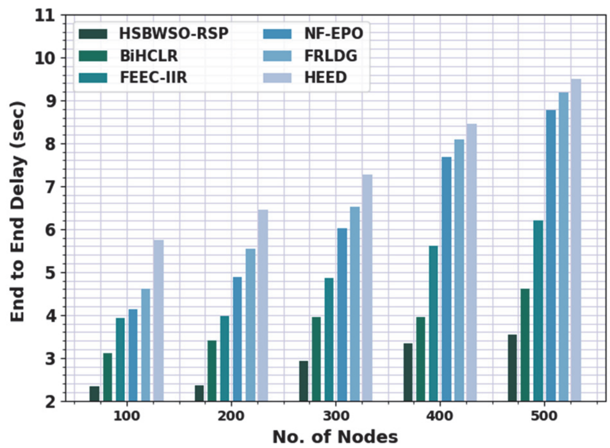

Figure 8 ETED analysis of HSBWSO-RSP system under distinct nodes

5 CONCLUSION

In this study, we have presented a new HSBWSO-RSP for multihop communication in IoT based WSN. The presented HSBWSO-RSP approach aims to properly determine the routes to destination for multihop communication. Moreover, the HSBWSO-RSP technique enables the integration of variance perturbation mechanism into the traditional BWSO algorithm. Furthermore, the selection of routes takes place by a fitness function comprising *RE* and distance *DIST*. The experimental result analysis of the HSBWSO-RSP approach is tested using a sequence of experiments and the results are studied under different measures. The comparison study revealed the betterment of the HSBWSO-RSP method over existing routing techniques. In future, data aggregation protocols can be devised to improve the overall efficiency of the IoT assisted WSN.

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Contact information:

S. BALAKRISHNAN
Assistant Professor in the Department of Electronics and Communication Engineering,
Vivekanandha College of Engineering for Women,
Tiruchengode, India.

K.VINOTH KUMAR, M.E., M.B.A., PhD, Post Doctoral Fellow, Professor
Department of Electronics & Communication Engineering,
SSM Institute of Engineering and Technology , Dindigul, Tamil Nadu, India
GSM: 9787367067
E-mail: vinodkumaran87@gmail.com