Design of Evolutionary Algorithm Based Unequal Clustering for Energy Aware Wireless Sensor Networks

Mohammed Altaf Ahmed¹, T. Satyanarayana Murthy², Fayadh Alenezi³, E. Laxmi Lydia⁴, Seifedine Kadry⁵,⁶,⁷, Yena Kim⁸ and Yunyoung Nam⁸,*

¹Department of Computer Engineering, College of Computer Engineering & Sciences, Prince Sattam Bin Abdulaziz University, Al-Kharj, 11942, Saudi Arabia
²Chaitanya Bharathi Institute of Technology, Hyderabad, Telangana, India
³Department of Electrical Engineering, College of Engineering, Jouf University, Sakaka 72388, Saudi Arabia
⁴Department of Computer Science and Engineering, Vignan’s Institute of Information Technology, Visakhapatnam, 530049, India
⁵Department of Applied Data Science, Noroff University College, Kristiansand, Norway
⁶Department of Electrical and Computer Engineering, Lebanese American University, Byblos, Lebanon
⁷Artificial Intelligence Research Center (AIRC), College of Engineering and Information Technology, Ajman University, Ajman, United Arab Emirates
⁸Department of ICT Convergence, Soochunhyang University, Asan 31538, Korea
*Corresponding Author: Yunyoung Nam. Email: ynam@sch.ac.kr

Received: 03 September 2022; Accepted: 23 November 2022; Published: 26 May 2023

Abstract: Wireless Sensor Networks (WSN) play a vital role in several real-time applications ranging from military to civilian. Despite the benefits of WSN, energy efficiency becomes a major part of the challenging issue in WSN, which necessitate proper load balancing amongst the clusters and serves a wider monitoring region. The clustering technique for WSN has several benefits: lower delay, higher energy efficiency, and collision avoidance. But clustering protocol has several challenges. In a large-scale network, cluster-based protocols mainly adapt multi-hop routing to save energy, leading to hot spot problems. A hot spot problem becomes a problem where a cluster node nearer to the base station (BS) tends to drain the energy much quicker than other nodes because of the need to implement more transmission. This article introduces a Jumping Spider Optimization Based Unequal Clustering Protocol for Mitigating Hotspot Problems (JSOUCP-MHP) in WSN. The JSO algorithm is stimulated by the characteristics of spiders naturally and mathematically modelled the hunting mechanism such as search, persecution, and jumping skills to attack prey. The presented JSOUCP-MHP technique mainly resolves the hot spot issue for maximizing the network lifespan. The JSOUCP-MHP technique elects a proper set of cluster heads (CHs) using average residual energy (RE) to attain this. In addition, the JSOUCP-MHP technique determines the cluster sizes based on two measures, i.e., RE and distance to BS (DBS), showing the novelty of the work. The proposed JSOUCP-MHP technique is examined under several experiments to ensure its supremacy. The comparison study shows the significance of the JSOUCP-MHP technique over other models.

This work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.
1 Introduction

Wireless Sensor Networks (WSNs) are advanced for monitoring and sensing vital signs of area and environment using linked and distributed sensor nodes (SNs). The SNs were divided into Gateway Nodes (GN), normal, and sink nodes [1]. The SNs were small in size and had insufficient sources concerning processing, storage, and space energy [2]. In many cases, the SNs were deployed in a very harsh and intense ecosystem. The first and foremost goal of this positioning was to sense information distantly and sends it to the system or user for decision-making. To send data, there comes a demand for more effective systems for managing the energy system of nodes and enhancing network lifetime [3]. The SNs perceive and sense the data from nearby environments, make processes, and transmit it to the nearby nodes until data arrives at the base station (BS). In WSN, because of the restricted energy sources of SNs, there comes a crucial need for a well-effective and balanced data aggregation system and energy-efficient routing protocol [4]. The energy feature becomes one factor to consider for devising any solution for WSNs. Numerous routing protocols were devised to conserve the energy of SNs [5]. The clustering approach becomes an effective topological control system that could efficiently enhance the scalability duration and lifetime of WSNs. The WSN applications have achieved popularity, including health monitoring, target tracking, disaster response, environmental monitoring, and security [6].

In a clustering ecosystem, data can be involved from one node to another and occurs energy holes or hotspot difficulties [7]. A hotspot can be made by SNs positioned nearby the BS and rapidly drain energy because traffic arises from other nodes and is sent from it. Such SNs not just transmit their data but also send it from other bases because the initial death of nodes causes hotspot problems. The methods, namely unequal clustering methods and mobile sinks or mobile data mules, were majorly utilized to resolve this problem [8]. But many unequal clustering techniques were devised for the solution of the hotspot leverages cluster, which is smaller in size adjacent to BS and cluster size rose case when we were going far away from BS. The cluster size was inversely proportional to the distance from BS. The clusters adjacent to BS hold a greater quantity of nodes that is helpful in efficient load sharing [9]. The projected method for size allotment and size difference of clusters leads to a reduction of frequency where a specific node turns out to be a cluster head (CH) [10]. This aids in the maintenance of the overall connectivity and thwarts network isolation. In line with this, hot spot issues can be reduced. One of the problems concerning unequal clustering was cluster size decreasing or increasing ratio that was not conferred in prevailing methods.

This article introduces a Jumping Spider Optimization Based Unequal Clustering Protocol for Mitigating Hotspot Problems (JSOUCP-MHP) in WSN. The JSO algorithm is stimulated by the characteristics of spiders in nature and mathematically modelled the hunting mechanism such as search, jumping skills, and persecution to attack prey. The presented JSOUCP-MHP technique mainly resolves the hot spot issue for maximizing the network lifespan. To attain this, the JSOUCP-MHP technique elects a proper set of cluster heads (CHs) using average RE. In addition, the JSOUCP-MHP technique determines the cluster sizes based on two measures i.e., RE and distance to BS (DBS). The proposed JSOUCP-MHP technique is examined under several experiments to ensure its supremacy.

2 Related Works

Arikumar et al. [11] modelled an Energy Efficient LifeTime Maximization (EELTM) technique that uses intelligent techniques of Fuzzy Inference System (FIS) and particle swarm optimization (PSO). In addition, an optimal CH–CR selecting method in this technique exploits fitness values (FV) computed by the PSO
approach for determining 2 optimal nodes in every cluster to serve as Cluster Router (CR) and CH. The CH, which is selected, exclusively accumulates the data from its cluster members. However, the CR is accountable for receiving the data collected from its CH and sending it to BS. Mehra [12] formulated an enhanced fuzzy unequal clustering and routing protocol (E-FUCA) in which vital variables were regarded at the time of CH candidate selection, and non-CH nodes considered intellectual decisions utilizing FL at the time of the election of its CH for forming clusters. FL is utilized as the next-hop choice for effective routing to expand the lifespan. And carried out the simulation experimentations for 4 cases, and a comparison was made with the propound performance of protocol with recent similar protocols.

Wang et al. [13] introduced an energy-efficient unequal clustering routing algorithm (UCRA). At first, the monitoring region was separated by concentric circles as rings of various sizes. Then, the CH was selected relating to RE and position. Before clustering, every typical sensor links cluster related to the electability of every CH. Nguyen et al. [14] presented a new optimization technique, like the compact bat algorithm (cBA), for using it for optimisation issues involving gadgets containing inadequate hardware sources. A real-valued prototype vector can be employed for probabilistic functions for generating every candidate solution for optimizing cBA. The projected cBA was widely assessed on numerous continual multi-modal functions and the unequal clustering of WSN (uWSN) issues.

In [15], competitive swarm optimization (CSO) related methods were introduced, together called such methods as CSO-UCRA. Initially, the CH selecting approach relies on CSO related approach after assigning non-CH sensors to CHs. At last, a CSO-related routing method was provided. New fitness functions and efficient particle encoding techniques were advanced for such methods. Guleria et al. [16] devise the new ant colony meta-heuristic related to unequal clustering for novel CH election. The neighbor finding level and link maintenance by Meta-Heuristic Ant Colony Optimization (ACO) technique choose the optimal path among the nodes that raises the packets distributed to the destiny. Though several models are available in the literature review, still much work is needed to resolve the hot spot problem. In addition, unequal clustering should be performed by the use of multiple input parameters.

3 The Proposed Unequal Clustering Protocol

This article presented a novel JSOUCP-MHP algorithm for resolving hot spot issues in WSN. The JSO algorithm is stimulated by the characteristics of spiders in nature and mathematically modelled the hunting mechanism such as search, jumping skills, and persecution to attack prey. The presented JSOUCP-MHP technique mainly resolves the hot spot issue for maximizing network lifespan. Fig. 1 depicts the overall process of the JSOUCP-MHP approach.

3.1 System Model

A WSN comprises $N$ uniform distribution sensors. There is one BS interconnected with users through the Internet. Let assume $S = \{s_1, s_2, ..., s_i, s_{N-1}, s_N\}$ as the group of nodes, whereby $s_i$ denotes a nodei and $|S| = N$. WNS makes use of wireless radio transceivers depending on the different variables, for example, energy utilization and distance. The distance between the receiver and transmitter, followed by attenuated transceiver power, exponentially reduced with increased distance. Now, we represent $(x_i, y_i)$ and $(x_j, y_j)$ were the coordinates of nodes $i$ and $j$. Assume node $i$ sent to destination node $j$, the energy consumed on communication over $d$ distance can be evaluated as follows:

$$E_{Tx_i(l, d)} = E_{Tx-elec}(l) + E_{Tx-amp}(l, d) = \begin{cases} I \times E_{elec} + \varepsilon_{fs} \times d^2, & d < d_0 \\ I \times E_{elec} + \varepsilon_{amp} \times d^4, & d \geq d_0 \end{cases}$$ (1)
In Eq. (1), E refers to the energy consumption; Tx is to transfer, elect, amp specifies electronic and amplify to modulate, digitalized coding, spreading, and filter signals. It illustrates that multi-hop transmission is highly efficient in WSN. $d_0$ denotes a threshold of space model,

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}},$$

(2)

In Eq. (2), the power loss $\varepsilon_{fs}/\varepsilon_{mp}$ are free space and multi-path model, and it is formulated by

$$E_{\text{Rx}(l)} = E_{\text{Rx-elec}}(l) = l \times E_{\text{elec}}.$$  

(3)

WSN considered N node in the region of 2D $M^2$ with k cluster. In relation to the hotspot, perplexity in WSN was balancing the load amongst CHs according to the clustering technique. Unequal clustering decreases the cluster size nearer to BS, and the size of the cluster rises as the distance between the BS ad well as CH rises. The cluster member senses the real-time parameter and transfers the sensed value to CH. CH aggregates and receives information to eliminate inessential information and transfer aggregated information to BS directly or through intermediatory CH. In equal clustering, the cluster size remains unchanged all over the network. But, in unequal clustering, the cluster size can be described according to the DBS [17]:

$$E_{\text{cluster}} = E_{CH} + \left(\frac{N}{k} - 1\right) \times E_{\text{member}}.$$  

(4)

Let $N/k - 1$ be the average of member nodes from the cluster, $E_{CH}$, $E_{\text{members}}$ denotes dissipated energy for CH and member correspondingly, and it is evaluated by:

$$E_{\text{member}} = l \times E_{\text{elec}} + l \times \varepsilon_{fs} \times d_{toCH}^2.$$  

(5)
As a result, the energy consumed for WSN from the generation formulated from the energy process and transceiver was given by:

$$E_{total} = E_p + E_{frame} = E_p + k \times E_{cluster}. \quad (7)$$

In Eq. (7), $E_p$ is the energy consumed for the microcontroller and source voltage of the node. It doesn’t affect the optimization process. As a result, the consumed energy $E_{frame}$ optimizes according to the distance for clustering optimization.

3.2 Design of JSO Algorithm

The mathematical modelling of the jumping spider’s hunting strategy is initially proposed. Then, The JSOA approach was introduced. The hunting strategies are searching, jumping on the prey, and attacking by persecution [18]. Also, the algorithm describes the pheromone rate of the spider as follows.

Once the spider is away from a distance, whereas it could catch the prey by jumping, it moves closer by indulging in certain stealthy movements till it is at an attainable distance where it can catch the prey and pounces on it. The persecution approach can be described as the uniform accelerated rectilinear motion.

$$x_i = \frac{1}{2}at^2 + v_0t \quad (8)$$

In Eq. (8), $x_i$ demonstrates the location of the $i^{th}$ follower spider, $t$ refers to the time, $v_0$ represents the speed initially. The acceleration can be shown as $a = \frac{v}{t}$ where $v = x - x_0$.

In this study, to optimize, every iteration can be regarded as the duration, in which the differences between iterations are equivalent to 1, and initially, the speed is fixed as zero, $v_0 = 0$. And it is formulated as follows:

$$x_{i(g+1)} = \frac{1}{2}(\vec{x}_i(g) - x_r(0)) \quad (9)$$

In Eq. (9), $\vec{x}_i(g + 1)$ represents the novel location of the search agent to generation $g + 1$, $\vec{x}_i(g)$ indicates the present $i^{th}$ searching agent in generation $g$, and $\vec{x}_r(0)$ denotes the $r^{th}$ searching agent arbitrarily chosen, with $i \neq r$, whereas $r$ represents an arbitrary value ranging from 1 to the size of maximal searching agent.

The jumping spider follows the prey and jumps on them. The hunting strategy of jumping on prey is characterized by a projectile motion.

$$\vec{x}_i = v_0 \cos (\varphi) \hat{u} \quad \frac{dx}{dt} = V_x = v_0 \cos (\varphi) \hat{r} \quad \quad (10)$$

Likewise, the vertical axis and the derivative w.r.t time can be given as.

$$\vec{y}_i = (v_0 \sin(\varphi) t_0^2 - gt^2) \hat{j} \quad \frac{dy}{dt} = V_y = (v_0 \sin(\varphi) - gt) \hat{j} \quad (11)$$
Similarly, time is characterized by strategy 1. Thus we attain the trajectory equation as follows.

\[ y = x \tan (x) - \frac{g x^2}{2 V_0^2 \cos^2(x)} \]  
(12)

Lastly, the trajectory is formulated by:

\[ x_i^{(g+1)} = x_i^{(g)} \tan (x) - \frac{g x^2 (g)}{2 V_0^2 \cos^2(x)} \]  
(13)

\[ x = \frac{\varphi \pi}{180} \]

In Eq. (13), \( x_i^{(g+1)} \) refers to the novel location of a searching agent, representing jumping spider movement, \( x_i^{(g)} \) denotes the existing \( i \)-th searching agent, \( V_0 \) is fixed as 100 mm/seg, \( g \) denotes the gravity (9.80665 m/s\(^2\)), and the \( x \) angle can be measured by a \( \varphi \) angle arbitrarily produced within zero and one.

The Jumping spider implements a random search around the environment to locate prey. Local and global search are the two mathematical functions presented as follows.

The local search can be defined as follows:

\[ x_i^{(g+1)} = x_{best}^{(g)} + \text{walk} - \left( \frac{1}{2} - \varepsilon \right) \]  
(14)

In Eq. (14), \( x_i^{(g+1)} \) refers to the novel location of the searching agent, \( x_{best}^{(g)} \) denotes the optimal searching agent found from the preceding iteration, the walk was a normally distributed pseudo-random integer within \((-2, 2)\), \( \varepsilon \) denotes a pseudo-random number uniformly distributing from \((0, 1)\).

At the same time, the Global search can be expressed as follows.

\[ x_i^{(g+1)} = x_{best}^{(g)} + \lambda \]  
(15)

In Eq. (15), \( x_i^{(g+1)} \) denotes the novel location of a searching agent, \( x_{best}^{(g)} \) and \( x_{worst}^{(g)} \) indicates the best and worst searching agent form preceding iteration; correspondingly, and \( \lambda \) refers to a Cauchy random integer with \( \mu \) fixed as 0 and \( \theta \) fixed as 1.

Pheromone is released by several animals, amongst which were insects, together with spiders. Nonetheless, they produce pheromones; the modelling of the rate of pheromones was taken and described as follows:

\[ \text{pheromone} (i) = \frac{\text{Fitness}_{\text{max}} - \text{Fitness}(i)}{\text{Fitness}_{\text{max}} - \text{Fitness}_{\text{min}}} \]  
(16)

In Eq. (16), \( \text{Fitness}_{\text{max}} \) and \( \text{Fitness}_{\text{min}} \) represent the worst and the best FV in the present generation, correspondingly, while \( \text{Fitness}(i) \) refers to the present FV of the \( i \)-th searching agent. Eq. (16) normalizes the FV within zero and one whereas 0 indicates the worst pheromone rate, while 1 denotes the optimal. The criteria involve for lower pheromone rate value equivalent to or lesser than 0.3 as follows:

\[ x_i^{(g)} = \overline{x}_{best}^{(g)} + \frac{1}{2} \left( x_{r_1}^{(g)} - ( -1)^{r_2} x_{r_2}^{(g)} \right) \]  
(17)

In Eq. (17), \( \overline{x}_i^{(g)} \) represent the searching agent (jumping spider) with a lower pheromone rate that is upgraded, \( r_1 \) and \( r_2 \) indicate arbitrary number produced from 1 to the maximal size of a searching agent,
with \( r_1 \neq r_2 \), while \( x_{r_1}\theta(g) \) and \( x_{r_2}\theta(g) \) are the \( r_1, r_2 \)th searching agent selected, \( x_{best}\theta(g) \) indicates the best searching agent from preceding iteration and \( \sigma \) indicates a binary number produced, \( \sigma \in \{0, 1\} \).

### 3.3 Process Involved in JSOUCP-MHP Technique

In the real-time application of WSN, a massive amount of nodes is positioned generally with a higher node density. Assume a proper threshold \( T \) for controlling the proportion of \( CH \), \( T \) is fixed at 0.4. Every node \( S_j \) evaluates the value of \( l \). When \( l < T \), node \( S_j \) become a CCH; or else, node \( S_j \) becomes a regular node and go to a dormant state until the last CH selection is accomplished as follows.

\[
l = l_0 \cdot E_{avg} \cdot R_{E_i}
\]

In Eq. (18), \( l_0 \) refers to a uniformly distributed arbitrary value within \([0, 1]\), and \( E_{avg} \) indicates the average RE of an alive node. The computation method was given in the following: The data packet transferred by the node includes \( R_{E_i} \). Afterward, the BS received, the average RE \( E_{avg} \) of each alive node is evaluated; \( R_{E_i} \) characterizes the RE of node \( S_j \). Clearly, the large of \( R_{E_i} \), the small of \( l \), hence the better possibility that \( S_j \) becomes a CH.

In the JSOUCP-MHP technique, consider the distance from CH to BS and ignore the energy. This might leads to a lower energy node being the CH, and afterward generating a cluster, the member in the cluster causes an increase in the energy usage of CH. As a result, a competitive radius considering distance and energy is presented, and the competitive radius for CH \( v_i \) is evaluated as follows.

\[
v_i \cdot R_{comp} = \left[1 - w_1 \frac{d_{max} - d(v_j, BS)}{d_{max} - d_{min}} - w_2 \left(1 - \frac{R_{E_{v_j}}}{E_0}\right)\right] \times R_{comp}^0
\]

In Eq. (5), \( d_{max} \) and \( d_{min} \) denotes the maximal and minimal distances from the alive node to the BS; correspondingly, \( d(v_j, BS) \) represents the distance from \( v_j \) to the BS, \( R_{E_{v_j}} \) indicates the RE of \( v_j \), \( w_1 \) and \( w_2 \) are constant within \([0, 1]\), and \( w_1 + w_2 = 1 \).

### 4 Performance Validation

A brief set of experimental analyses is carried out to demonstrate the enhanced performance of the JSOUCP-MHP model on WSN. The initial energy is 1 mJ, the node count is 500, and first-order radio energy model is used.

Table 1 and Fig. 2 showcase the network lifetime (NLT) inspection of the JSOUCP-MHP model with existing models under the varying density of sensor nodes (DSN). The experimental outcomes depicted that the JSOUCP-MHP model has shown enhanced performance with higher NLT values. For instance, with 50 DSN, the JSOUCP-MHP model has exhibited an increased NLT of 1757 whereas the enhanced metaheuristic-driven energy-aware cluster-based routing (IMD-EACBR), sunflower optimization (SFO), grey wolf optimization (GWO), and genetic algorithm (GA) models have demonstrated reduced NLT of 1549, 1433, 1422, and 1343 respectively. Moreover, with 250 DSN, the JSOUCP-MHP model has attained a higher NLT of 2556, whereas the IMD-EACBR, SFO, GWO, and GA models have obtained lower NLT of 2374, 2276, 2012, and 1852 respectively. On the other hand, with 500 DSN, the JSOUCP-MHP model has illustrated an improved NLT of 3802, whereas the IMD-EACBR, SFO, GWO, and GA models have depicted reduced NLT of 3789, 3691, 3650, and 3369 respectively.

Table 2 and Fig. 3 exhibits the number of Alive Sensor Nodes (NOASN) analysis of the JSOUCP-MHP algorithm with existing models under varying count of rounds. The experimental outcomes depicted that the JSOUCP-MHP approach has shown enhanced performance with higher NOASN values. For example, with 2000 rounds, the JSOUCP-MHP approach has exhibited improved NOASN of 481 where the IMD-EACBR,
SFO, GWO, and GA methods have demonstrated reduced NOASN of 473, 405, 391, and 283 correspondingly. Furthermore, with 3000 rounds, the JSOUCP-MHP method has reached a higher NLT of 367 whereas the IMD-EACBR, SFO, GWO, and GA models have acquired lower NOASN of 264, 112, 80, and 78 correspondingly. In contrast, with 4000 rounds, the JSOUCP-MHP model has demonstrated an improved NOASN of 176 whereas the IMD-EACBR, SFO, GWO, and GA models have shown reduced NOASN of 87, 11, 0, and 0 correspondingly.

**Table 1:** NLT analysis of JSOUCP-MHP approach with recent algorithms under distinct DSNs

<table>
<thead>
<tr>
<th>Density of sensor nodes</th>
<th>JSOUCP-MHP</th>
<th>IMD-EACBR</th>
<th>SFO algorithm</th>
<th>GWO algorithm</th>
<th>Genetic algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>1757</td>
<td>1549</td>
<td>1433</td>
<td>1422</td>
<td>1343</td>
</tr>
<tr>
<td>100</td>
<td>1923</td>
<td>1789</td>
<td>1679</td>
<td>1504</td>
<td>1416</td>
</tr>
<tr>
<td>150</td>
<td>2160</td>
<td>2038</td>
<td>1773</td>
<td>1733</td>
<td>1611</td>
</tr>
<tr>
<td>200</td>
<td>2530</td>
<td>2171</td>
<td>2133</td>
<td>1870</td>
<td>1668</td>
</tr>
<tr>
<td>250</td>
<td>2556</td>
<td>2374</td>
<td>2276</td>
<td>2012</td>
<td>1852</td>
</tr>
<tr>
<td>300</td>
<td>2832</td>
<td>2666</td>
<td>2599</td>
<td>2468</td>
<td>2062</td>
</tr>
<tr>
<td>350</td>
<td>3104</td>
<td>2967</td>
<td>2852</td>
<td>2715</td>
<td>2354</td>
</tr>
<tr>
<td>400</td>
<td>3282</td>
<td>3145</td>
<td>3059</td>
<td>3050</td>
<td>2613</td>
</tr>
<tr>
<td>450</td>
<td>3487</td>
<td>3452</td>
<td>3418</td>
<td>3340</td>
<td>2976</td>
</tr>
<tr>
<td>500</td>
<td>3802</td>
<td>3789</td>
<td>3691</td>
<td>3650</td>
<td>3369</td>
</tr>
</tbody>
</table>

**Figure 2:** NLT analysis of JSOUCP-MHP approach under distinct DSNs
Table 2: NOASN analysis of JSOUCP-MHP approach with recent algorithms under distinct rounds

<table>
<thead>
<tr>
<th>No. of rounds</th>
<th>JSOUCP-MHP</th>
<th>IMD-EACBR</th>
<th>SFO algorithm</th>
<th>GWO algorithm</th>
<th>Genetic algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>481</td>
<td>473</td>
<td>405</td>
<td>391</td>
<td>283</td>
</tr>
<tr>
<td>2250</td>
<td>468</td>
<td>386</td>
<td>343</td>
<td>267</td>
<td>182</td>
</tr>
<tr>
<td>2500</td>
<td>451</td>
<td>393</td>
<td>230</td>
<td>216</td>
<td>125</td>
</tr>
<tr>
<td>2750</td>
<td>435</td>
<td>317</td>
<td>175</td>
<td>135</td>
<td>96</td>
</tr>
<tr>
<td>3000</td>
<td>367</td>
<td>264</td>
<td>86</td>
<td>80</td>
<td>78</td>
</tr>
<tr>
<td>3250</td>
<td>289</td>
<td>168</td>
<td>49</td>
<td>26</td>
<td>19</td>
</tr>
<tr>
<td>3500</td>
<td>245</td>
<td>133</td>
<td>19</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>3750</td>
<td>204</td>
<td>109</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>4000</td>
<td>176</td>
<td>87</td>
<td>11</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 3: NOASN analysis of JSOUCP-MHP approach under distinct rounds

A detailed number of dead sensor node (NODSN) assessments of the JSOUCP-MHP with recent approaches were performed in Table 3 and Fig. 4. The results inferred the JSOUCP-MHP technique has resulted in enhanced results with minimum values of NODSN. For instance, with 2000 rounds, the JSOUCP-MHP model has achieved the least NODN of 19 whereas the IMD-EACBR, SFO, GWO, and GA models have reached increased NODN of 27, 95, 109, and 217 respectively. Meanwhile, with 3000 rounds, the JSOUCP-MHP model has resulted in decreased NODN of 133 whereas the IMD-EACBR, SFO, GWO, and GA models have exhibited increased NODN of 236, 388, 420, and 422 respectively. Eventually, with 4000 rounds, the JSOUCP-MHP method has rendered a minimal NODN of 324 whereas the IMD-EACBR, SFO, GWO, and GA models have achieved maximum NODN of 413, 489, 500, and 500 correspondingly.
A detailed energy consumption (ECON) evaluation of the JSOUCP-MHP with recent methods is executed in Table 4 and Fig. 5. The results implicit the JSOUCP-MHP method have resulted in enhanced results with the least values of ECON. For example, with 50 DSN, the JSOUCP-MHP method del has gained the least ECON of 0.0585 mJ whereas the IMD-EACBR, SFO, GWO, and GA models have acquired increased ECON of 0.0936, 0.1117, 0.1373, and 0.2183 mJ correspondingly. In the meantime, with 250 DSN, the JSOUCP-MHP algorithm has resulted in decreased ECON of 0.3004 mJ whereas the IMD-EACBR, SFO, GWO, and GA algorithms have exhibited improved ECON of 0.3201, 0.4321, 0.5201, and 0.5545 mJ respectively. Finally, with 500 DSN, the JSOUCP-MHP model has presented a minimal ECON of 0.5437 mJ whereas the IMD-EACBR, SFO, GWO, and GA models have gained maximum NODN of 0.6608, 0.6678, 0.8210, and 0.8433 mJ correspondingly.

Table 3: NODSN analysis of JSOUCP-MHP approach with recent algorithms under distinct rounds

<table>
<thead>
<tr>
<th>No. of rounds</th>
<th>JSOUCP-MHP</th>
<th>IMD-EACBR</th>
<th>SFO algorithm</th>
<th>GWO algorithm</th>
<th>Genetic algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>2000</td>
<td>19</td>
<td>27</td>
<td>95</td>
<td>109</td>
<td>217</td>
</tr>
<tr>
<td>2250</td>
<td>32</td>
<td>114</td>
<td>157</td>
<td>233</td>
<td>318</td>
</tr>
<tr>
<td>2500</td>
<td>49</td>
<td>107</td>
<td>270</td>
<td>284</td>
<td>375</td>
</tr>
<tr>
<td>2750</td>
<td>65</td>
<td>183</td>
<td>325</td>
<td>365</td>
<td>404</td>
</tr>
<tr>
<td>3000</td>
<td>133</td>
<td>236</td>
<td>388</td>
<td>420</td>
<td>422</td>
</tr>
<tr>
<td>3250</td>
<td>211</td>
<td>332</td>
<td>414</td>
<td>441</td>
<td>459</td>
</tr>
<tr>
<td>3500</td>
<td>255</td>
<td>367</td>
<td>451</td>
<td>474</td>
<td>481</td>
</tr>
<tr>
<td>3750</td>
<td>296</td>
<td>391</td>
<td>481</td>
<td>500</td>
<td>500</td>
</tr>
<tr>
<td>4000</td>
<td>324</td>
<td>413</td>
<td>489</td>
<td>500</td>
<td>500</td>
</tr>
</tbody>
</table>

Figure 4: NODSN analysis of JSOUCP-MHP approach under distinct rounds
Table 5 and Fig. 6 display the throughput (THROU) review of the JSOUCP-MHP model with existing models under varying DSN. The experimental outcomes indicated the JSOUCP-MHP model has shown enhanced performance with higher THROU values. For example, with 50 DSN, the JSOUCP-MHP method has exhibited an increased THROU of 0.9875 Mbps whereas the IMD-EACBR, SFO, GWO, and GA models have demonstrated reduced THROU of 0.9323, 0.8915, 0.8640, and 0.8136 Mbps correspondingly. In addition, with 250 DSN, the JSOUCP-MHP model has gained higher THROU of 0.9517 Mbps whereas the IMD-EACBR, SFO, GWO, and GA models have obtained lower THROU of 0.8955, 0.7997, 0.7435, and 0.7031 Mbps correspondingly.

<table>
<thead>
<tr>
<th>The density of sensor nodes</th>
<th>JSOUCP-MHP</th>
<th>IMD-EACBR</th>
<th>SFO algorithm</th>
<th>GWO algorithm</th>
<th>Genetic algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0.0585</td>
<td>0.0936</td>
<td>0.1117</td>
<td>0.1373</td>
<td>0.2183</td>
</tr>
<tr>
<td>100</td>
<td>0.1199</td>
<td>0.1467</td>
<td>0.2031</td>
<td>0.2171</td>
<td>0.3396</td>
</tr>
<tr>
<td>150</td>
<td>0.1074</td>
<td>0.1851</td>
<td>0.2507</td>
<td>0.3078</td>
<td>0.4064</td>
</tr>
<tr>
<td>200</td>
<td>0.2350</td>
<td>0.2729</td>
<td>0.3578</td>
<td>0.4194</td>
<td>0.5030</td>
</tr>
<tr>
<td>250</td>
<td>0.3004</td>
<td>0.3201</td>
<td>0.4231</td>
<td>0.5201</td>
<td>0.5545</td>
</tr>
<tr>
<td>300</td>
<td>0.3910</td>
<td>0.4030</td>
<td>0.5945</td>
<td>0.5585</td>
<td>0.6187</td>
</tr>
<tr>
<td>350</td>
<td>0.4355</td>
<td>0.4941</td>
<td>0.5978</td>
<td>0.6704</td>
<td>0.6951</td>
</tr>
<tr>
<td>400</td>
<td>0.5019</td>
<td>0.5108</td>
<td>0.6196</td>
<td>0.6940</td>
<td>0.7837</td>
</tr>
<tr>
<td>450</td>
<td>0.5228</td>
<td>0.5598</td>
<td>0.6437</td>
<td>0.7575</td>
<td>0.8135</td>
</tr>
<tr>
<td>500</td>
<td>0.5437</td>
<td>0.6088</td>
<td>0.6678</td>
<td>0.8210</td>
<td>0.8433</td>
</tr>
</tbody>
</table>

Figure 5: ECON analysis of JSOUCP-MHP approach under distinct DSNs

Table 4: ECON analysis of JSOUCP-MHP approach with recent algorithms under distinct DSNs

Figure 5: ECON analysis of JSOUCP-MHP approach under distinct DSNs

Table 5 and Fig. 6 display the throughput (THROU) review of the JSOUCP-MHP model with existing models under varying DSN. The experimental outcomes indicated the JSOUCP-MHP model has shown enhanced performance with higher THROU values. For example, with 50 DSN, the JSOUCP-MHP method has exhibited an increased THROU of 0.9875 Mbps whereas the IMD-EACBR, SFO, GWO, and GA models have demonstrated reduced THROU of 0.9323, 0.8915, 0.8640, and 0.8136 Mbps correspondingly. In addition, with 250 DSN, the JSOUCP-MHP model has gained higher THROU of 0.9517 Mbps whereas the IMD-EACBR, SFO, GWO, and GA models have obtained lower THROU of 0.8955, 0.7997, 0.7435, and 0.7031 Mbps correspondingly.
Conversely, with 500 DSN, the JSOUCP-MHP model has exemplified enhanced THROU of 0.8910 Mbps whereas the IMD-EACBR, SFO, GWO, and GA models have depicted reduced NLT of 0.8054, 0.7161, 0.5999, and 0.5500 Mbps correspondingly.

A detailed Packet Loss Rate (PLR) valuation of the JSOUCP-MHP with recent methods is exhibited in Table 6 and Fig. 7. The results denoted the JSOUCP-MHP approach has resulted in enhanced results with the least values of PLR. For example, with 50 DSN, the JSOUCP-MHP model has attained least PLR of 0.94% whereas the IMD-EACBR, SFO, GWO, and GA models have gained increased PLR of 1.78%, 3.69%, 3.88%, and 4.96% correspondingly.

**Table 5:** THROU analysis of JSOUCP-MHP approach with recent algorithms under distinct DSNs

<table>
<thead>
<tr>
<th>The density of sensor nodes</th>
<th>JSOUCP-MHP</th>
<th>IMD-EACBR</th>
<th>SFO algorithm</th>
<th>GWO algorithm</th>
<th>Genetic algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0.9875</td>
<td>0.9323</td>
<td>0.8915</td>
<td>0.8640</td>
<td>0.8136</td>
</tr>
<tr>
<td>100</td>
<td>0.9660</td>
<td>0.9313</td>
<td>0.8776</td>
<td>0.8069</td>
<td>0.7964</td>
</tr>
<tr>
<td>150</td>
<td>0.9598</td>
<td>0.9247</td>
<td>0.8578</td>
<td>0.7831</td>
<td>0.7724</td>
</tr>
<tr>
<td>200</td>
<td>0.9562</td>
<td>0.9038</td>
<td>0.8404</td>
<td>0.7701</td>
<td>0.7398</td>
</tr>
<tr>
<td>250</td>
<td>0.9517</td>
<td>0.8955</td>
<td>0.7997</td>
<td>0.7435</td>
<td>0.7031</td>
</tr>
<tr>
<td>300</td>
<td>0.9489</td>
<td>0.8794</td>
<td>0.7833</td>
<td>0.7071</td>
<td>0.6677</td>
</tr>
<tr>
<td>350</td>
<td>0.9405</td>
<td>0.8445</td>
<td>0.7661</td>
<td>0.6900</td>
<td>0.6286</td>
</tr>
<tr>
<td>400</td>
<td>0.9337</td>
<td>0.8307</td>
<td>0.7389</td>
<td>0.6651</td>
<td>0.6032</td>
</tr>
<tr>
<td>450</td>
<td>0.9123</td>
<td>0.8180</td>
<td>0.7275</td>
<td>0.6325</td>
<td>0.5766</td>
</tr>
<tr>
<td>500</td>
<td>0.8910</td>
<td>0.8054</td>
<td>0.7161</td>
<td>0.5999</td>
<td>0.5500</td>
</tr>
</tbody>
</table>

**Figure 6:** THROU analysis of JSOUCP-MHP approach under distinct DSNs

Conversely, with 500 DSN, the JSOUCP-MHP model has exemplified enhanced THROU of 0.8910 Mbps whereas the IMD-EACBR, SFO, GWO, and GA models have depicted reduced NLT of 0.8054, 0.7161, 0.5999, and 0.5500 Mbps correspondingly.

A detailed Packet Loss Rate (PLR) valuation of the JSOUCP-MHP with recent methods is exhibited in Table 6 and Fig. 7. The results denoted the JSOUCP-MHP approach has resulted in enhanced results with the least values of PLR. For example, with 50 DSN, the JSOUCP-MHP model has attained least PLR of 0.94% whereas the IMD-EACBR, SFO, GWO, and GA models have gained increased PLR of 1.78%, 3.69%, 3.88%, and 4.96% correspondingly.
Meanwhile, with 250 DSN, the JSOUCP-MHP model has resulted in decreased PLR of 1.79% whereas the IMD-EACBR, SFO, GWO, and GA models have exhibited increased PLR of 2.67%, 4.68%, 4.89%, and 5.57% correspondingly. Finally, with 500 DSN, the JSOUCP-MHP model has offered a lesser PLR of 2.89% whereas the IMD-EACBR, SFO, GWO, and GA models have acquired maximum PLR of 3.69%, 5.71%, 5.85%, and 6.72% correspondingly. These results confirmed that the JSOUCP-MHP technique has accomplished enhanced performance over other models.

### Table 6: PLR analysis of JSOUCP-MHP approach with recent algorithms under distinct DSNs

<table>
<thead>
<tr>
<th>Density of sensor nodes</th>
<th>JSOUCP-MHP</th>
<th>IMD-EACBR</th>
<th>SFO algorithm</th>
<th>GWO algorithm</th>
<th>Genetic algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>50</td>
<td>0.94</td>
<td>1.78</td>
<td>3.69</td>
<td>3.88</td>
<td>4.96</td>
</tr>
<tr>
<td>100</td>
<td>1.11</td>
<td>2.02</td>
<td>3.99</td>
<td>4.17</td>
<td>5.08</td>
</tr>
<tr>
<td>150</td>
<td>1.38</td>
<td>2.19</td>
<td>4.22</td>
<td>4.35</td>
<td>5.22</td>
</tr>
<tr>
<td>200</td>
<td>1.51</td>
<td>2.48</td>
<td>4.39</td>
<td>4.64</td>
<td>5.38</td>
</tr>
<tr>
<td>250</td>
<td>1.79</td>
<td>2.67</td>
<td>4.68</td>
<td>4.89</td>
<td>5.57</td>
</tr>
<tr>
<td>300</td>
<td>2.02</td>
<td>2.77</td>
<td>4.91</td>
<td>5.06</td>
<td>5.85</td>
</tr>
<tr>
<td>350</td>
<td>2.14</td>
<td>2.98</td>
<td>5.17</td>
<td>5.20</td>
<td>6.11</td>
</tr>
<tr>
<td>400</td>
<td>2.40</td>
<td>3.11</td>
<td>5.37</td>
<td>5.79</td>
<td>6.24</td>
</tr>
<tr>
<td>450</td>
<td>2.65</td>
<td>3.40</td>
<td>5.58</td>
<td>5.80</td>
<td>6.48</td>
</tr>
<tr>
<td>500</td>
<td>2.89</td>
<td>3.69</td>
<td>5.71</td>
<td>5.85</td>
<td>6.72</td>
</tr>
</tbody>
</table>

**Figure 7:** PLR analysis of JSOUCP-MHP approach under distinct DSNs
5 Conclusion

In this article, a novel JSOUCP-MHP system has been presented for resolving hot spot issues in WSN. The JSO algorithm is stimulated by the characteristics of spiders naturally and mathematically modelled the hunting mechanism such as jumping skills, persecution, and search, to attack prey. The presented JSOUCP-MHP technique mainly resolves the hot spot issue for maximizing the network lifetime. To attain this, the JSOUCP-MHP technique elects proper set of CHs using average RE. Also, the JSOUCP-MHP system determines the cluster sizes dependent upon two measures such as RE and DBS. The proposed JSOUCP-MHP technique is examined under several experiments to ensure its supremacy. The comparison study shows the significance of the JSOUCP-MHP technique over other models. In upcoming years, the performance of the JSOUCP-MHP system will be improved by data aggregation approaches.

Funding Statement: This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ICAN (ICT Challenge and Advanced Network of HRD) program (IITP-2022-2020-0-01832) supervised by the IITP (Institute of Information & Communications Technology Planning & Evaluation) and the Korea Technology and Information Promotion Agency (TIPA) for SMEs grant funded by the Korea government (Ministry of SMEs and Startups) (No. S3271954) and the Soonchunhyang University Research Fund.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References


