Artificial Intelligence Review (2025) 58:79
https://doi.org/10.1007/s10462-024-11088-4

Enhancing wireless sensor network lifespan and efficiency through improved cluster head selection using improved squirrel search algorithm

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Accepted: 23 December 2024 / Published online: 6 January 2025

Abstract
A Wireless Sensor Network (WSN) is a significant technological advancement that might contribute to the industrial revolution. The sensor nodes that are part of WSNs are battery-powered. Energy is the most crucial resource for WSNs since batteries cannot be changed or refilled. Since WSNs are a finite resource, several techniques have been devised and used throughout time to preserve them. To extend the lifespan of WSNs, this study will provide an effective method for Cluster Head (CH) selections. Many researches are employing the Swarm-based optimization algorithm to Select the optimal CH. In this study, the Squirrel Search Algorithm (SSA) is utilized to select the optimal CH Selection in WSN. The general SSA has been modified in this study to address the exact need for CH choice in WSNs. The Improved Squirrel Search Algorithm (I-SSA) integrates a series of enhancements aimed at accelerating convergence and elevating solution quality. Notably, we've implemented Adaptive Population Initialization, Dynamic Step Size Control, and a Local Search Algorithm to augment the exploration and exploitation capabilities of the SSA. These enhancements collectively refine the algorithm's ability to navigate the search space effectively, resulting in more efficient convergence towards optimal solutions. The suggested formulation's goal function takes into account the CH balance average, factor, sink distance residual energy and intra-cluster distance. The simulations are run under a variety of circumstances. The MATLAB 2021a working setting is utilised for simulation. The proposed code of conduct SSA-C is compared with the existing protocols Grey Wolf Optimization (GWO), SSA, Chernobyl Disaster Optimizer (CDO), Sperm Swarm Optimization (SSO), A Metaheuristic Optimized Cluster head selection-based Routing Algorithm for WSNs (MOCRAW), Energy-Efficient Weighted Clustering (EEWC), and Multi-agent pathfinding using Ant Colony Optimization (MAP-ACO). The ISSA-C method achieved a Packet Delivery Ratio (PDR) of 88%, outperforming GWO, SSA, and MAP-ACO. It reduced energy consumption to 210 mJ, which is lower than other methods, and showed improved bit error rates. Cluster formation and head selection times were also reduced to 82 s and 67 s, respectively.

Keywords Routing protocol · Wireless Sensor Networks · Squirrel search algorithm · Clustering

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Abbreviations

WSN	Wireless Sensor Network
CH	Cluster Head
SSA	Squirrel Search Algorithm
I-SSA	Improved Squirrel Search Algorithm
PDR	Packet Delivery Ratio
BER	Bit Error Rate
E2ED	End-to-End Delay
GWO	Grey Wolf Optimization
CDO	Chernobyl Disaster Optimizer
SSO	Sperm Swarm Optimization
MOCRAW	Metaheuristic Optimized Cluster head selection-based Routing Algorithm for WSNs
EEWC	Energy-Efficient Weighted Clustering
MAP-ACO	Multi-agent pathfinding using Ant Colony Optimization
SN	Sensor Node
BS	Base Station
MATLAB	Matrix Laboratory (software)
NFL	No Free Lunch Theorem
DSBCA	Distributed Self-Organization Balanced Clustering Algorithm
PSO	Particle Swarm Optimization
CRO	Chemical Reaction Optimization
FRLDG	Tree-based Resilient Cluster Header-based Solution
TCBDGA	Tree Group-based Data Collection with Mobile Sink
QOL	Quasi-Oppositional Learning
EHO	Enhanced Harmony Optimization
F-CNR	Fuzzy-based Continuous Node Refinement
FS	Flying Squirrel

1 Introduction

One of the most effective techniques for receiving, analysing, and delivering data from remote locations to the main data handling centres is WSNs (Akyildiz et al. 2002). As an advanced and distinctive data collection and processing technique, WSN has a broad multiplicity of uses in environmental monitoring, military, smart furniture, space exploration, and other fields. They are used for many different things, including broadcasting, routing, and forwarding. Thousands of small, independent sensor nodes with low battery capacities make up a typical WSN. Batteries cannot be easily replaced since these sensor nodes are often positioned in remote areas. Therefore, it becomes crucial to replace their energy. It is crucial to maintain the nodes' energy before moving on to energy replenishment. This is when WSNs' ability to save energy is put to use. It's crucial to reduce energy losses if a WSN is to remain operational. To do this, clustering offers an effective and sufficiently basic strategy.

When a large number of WSN nodes are combined and the clustering is done, where communication can be done between the clustering and the BS through the CH, this is generally called clustering (Younis et al. 2006). Choosing the clusters and the appropriate CHs is in itself a daunting and scary process. Over time, different methods have been used in the selection of CHs in the most optimal way.

Various optimization strategies (Forster and Venayagamoorthy 2011) are being utilized over time to identify the optimal CHs in the network. To facilitate CH selection, the literature has suggested various metaheuristic approaches inspired by nature. These optimization approaches, as discussed in the literature (Forster and Venayagamoorthy 2011), are focused on improving the CH selection processes' efficiency. Scholars have actively investigated and explored this objective to create and use a range of metaheuristic algorithms derived from nature. These algorithms are based on the natural processes of the world, biological systems as well as social behaviours to design new ways of solving difficult optimization problems. These metaheuristic approaches use concepts from nature like swarm intelligence, evolutionary process, and behaviour of colonies and hence provide new solutions to the CH selection problem in WSNs. These well-liked metaheuristic algorithms have pros and cons when applied to the process of choosing a cluster head. Also, it is important to note that there is always a superior optimization strategy to the one currently being employed as stated in the No Free Lunch (NFL) Theorem.

The motivation for this study stems from the necessity for energy efficiency in WSNs. WSNs are one of the most promising technologies that can be introduced to create new opportunities for numerous industries. However, WSNs are made up of sensor nodes that are usually powered by batteries; therefore, power conservation is normally a major consideration. Unlike conventional power sources, batteries in WSNs cannot be easily replaced or refilled, making efficient energy utilization imperative for prolonging network lifespan. To address this challenge and extend the longevity of WSNs, this study focuses on devising an effective method for CH selection. In WSNs, cluster heads are essential because they collect data from SNs and provide it to the base stations.

The ISSA-C protocol is suggested in this research as a means of extending the period of sensor networks. This ISSA-C is considered at every stage of the data gathering and dissemination process for picking out the energy-efficient CH. Only one possible SN—the cluster head—is selected by employing the sailing factor as an anchor. As it investigates the search space's answers about three dimensions, it prevents the cluster head from being often selected. This research employs SSA optimization in contrast to the existing CH selection algorithms. In SSA, the squirrels hop from one location to a different location in pursuit of the global best location. Additionally, unlike PSO, the SSA shows a significant convergence property. The suggested ISSA-C approach takes use of SSA's strong convergence, high search efficiency, and dynamic property to select energy-efficient CHs for the WSNs. This paper makes significant advances to the energy-efficient routing protocol for wireless sensor networks and I-SSA-based clustering:

- This work introduces a novel technique for selecting WSN group leaders using the I-SSA. The extension of I-SSA such as Adaptive Population Initialization, Dynamic Step Size Control and Local Search Algorithm help to increase the algorithm's speed and accuracy to select group heads.
- The proposed method, known as ISSA-C, displays a great saving in terms of energy usage, which is 210 mJ in a network of one thousand sensor nodes. This is quite an improvement over other methods that require between 220 and 320 MJ. Therefore, the proposed ISSA-C method reduces energy consumption, thus increasing the functional-

ity time of WSNs.

- It is evident from the study that the ISSA-C technique is more effective in terms of several crucial criteria. It obtained a PDR of 88% and a better performance compared to other methods such as GWO, SSA and MAP-ACO. It decreases the BER to 10 ms, E2ED to 10 ms, cluster formation time to 82 s and time taken to select head node 67 s.
- This paper offers a comparison of the ISSA-C method with existing protocols including GWO, CDO, SSO, MOCRAW, EEWC, and MAP-ACO. This comparison demonstrates the advantage of ISSA-C in enhancing the network performance measures including the network lifetime, throughput as well as buffer usage.
- The simulations are performed using MATLAB 2021a, which provides a sound application for evaluating the proposed technique. The results of the simulation help demonstrate the ISSA-C method's efficacy in real-world applications to boost network dependability and efficiency.

The rest of the paper is structured as follows: Sect. 2 explains the literature review. The description of the typical SSA is the main topic of Sect. 3. The suggested ISSA-based CH selection procedure is described in Sect. 4. Section 5 provides the findings and the talk. Section 6 provides a discussion of the results such as the limitations, the problem of scalability, and the implication of the findings. The study paper's conclusion and discussion on the next steps are included in Sect. 7.

2 Literature review

This section evaluates the significant meta-heuristic cluster head algorithms that have been currently published or are available in this literature, highlighting both their advantages and disadvantages. One of the earliest clustering algorithms proposed in the literature is LEACH by Heinzelman et al. (Heinzelman et al. 2000). It operates in rounds and elect's CHs in each round via a decentralized probabilistic approach. Each SN selects an arbitrary integer between 0 and 1. The SN declares itself as a CH for a current round if the amount is below a threshold T (n). The bound is dependent on the no. of times the SN has served as a CH thus far and a preset proportion of CHs in the system. Each non-CH SN chooses its CH according to the signal strength it receives, i.e., it selects the CH that can be accessed with the least amount of transmission energy.

Distributed Self-Organization Balanced Clustering Algorithm (DSBCA) for WSN (Ying Liao et al. 2013) focuses on WSN with randomized distribution of SNs for load balancing, in contrast to the bulk of existing clustering methods that assume uniform distribution of the network's nodes. In DSBCA, a few randomly chosen SNs that eventually become temporary CHs start the process of electing new CHs. According to its space from the BS and the dispersion of its nodes, each temporary CH determines its cluster radius, k. Additionally, it determines a weight that accounts for the SN remaining energy, density, and times of election as CH. The interim CH which has the most weight among its k-hop neighbours is then chosen as the ultimate CH.

Additionally, several optimization methods are utilised to address the WSN problem. One of these, known as particle swarm optimization (PSO), has the benefit of offering a better solution while being more computationally efficient. The sensor node that is closer to the BS in the proposed PSO clustering is selected as the CH.

Another protocol that selects the CHs by taking into account residual energy and node distance is PSO-C (Kulkarni and Venayagamoorthy 2011). When contrasted to LEACH-C and LEACH, PSO performs healthier in throughput and network lifespan. As a result of PSO and graph theory, another protocol is suggested. With the help of the remaining energy and the distance, a weighted function is calculated. PSO may also be used to expand the reach of mobile WSNs. PSO is used to deploy sensor nodes. A key factor in determining how much energy is consumed by the network is intra-cluster distance. The best CHs with the smallest intra-cluster distance are chosen using a PSO-based CH excerption method.

Based on the innovative chemical reaction optimization (CRO), another method is suggested (Rao and Banka 2017). The network has a longer lifespan. The same author also suggests a PSO-based protocol for time-sensitive applications. It extends the network's life and takes energy use into account. The PSO-ECHS protocol, which takes into account remaining energy, intracluster distance, and sink distance, is suggested. The PSO is used. Nevertheless, it consumes a lot of energy since The burden is not balanced by forming equal clusters (Rao et al. 2017).

The grey wolf optimizer-based FIGWO technique is suggested in (Zhao et al. 2018). To choose the CHs, a fitness function is computed. Thanks to this fitness function, the node with the most energy and the one closest to the base station will both have a higher chance of being chosen as the CH. Whenever a novel CH is chosen, the distance needed to transmit information is likewise adjusted. However, it has trouble distributing the workload among the CHs.

For WSNs with mobile sinks (MS), Zhu et al. (Zhu et al. 2015) suggested a tree group-based data collection technique. To facilitate condensing, this study presents TCBDGA, a TCBDGA with a mobile washbasin. The authors proposed a dispersed method that selects a rendezvous node (RN) and positions it close to the MS after creating a cluster configuration. This technique's cluster system creates a cluster structure with varying sizes. Along the MS route, the distance between cluster heads is inversely correlated with each cluster's size. The proposed protocol minimises network power consumption and has several applications, including engineering environments given a vast quantity of disparate sensory data.

For big and dense WSN Internet of Things devices, Daniel et al. (Daniel et al. 2021) created a tree-based resilient cluster header-based solution using three parameters: bisection indexing, neighbourhood repetition, and algebraic connections. Every cluster detected in a dispersed WSN's data-gathering SNs is taken into consideration by the FRLDG-based approach that is provided in this study. The authors also spoke about all-groups trees and mobile sync nodes, Then they talked about the process of selecting a cluster head using residual energy, range, and latency.

Using a quasi-oppositional firefly algorithm as assistance, Preeth et al. (Preeth et al. 2018) developed an energy-efficient fuzzy logic cluster for the WSN method. A virtually opposite learning type II fuzzy logic-based cluster formation and firefly routing scheme for the WSN IoT network is the technique developed in this study. The optimum result set is produced by inserting quasi-opposite learning (QOL) into the firefly (FF) process to accelerate convergence.

In an IoT network, Khan et al. (Khan et al. 2018) reported energy enhancement utilising a distance-based PR-LEACH routing algorithm. This study tries to employ routing protocols to cut down on energy usage. The suggested procedure performs noticeably finer than the original procedure. The suggested procedure turns the over-all threshold calculation approach into a local threshold calculation, which makes it different from its parent protocol. The added functionality makes the chosen protocol more dynamic and efficient. IoT networks benefit from the upgraded protocol since it uses less energy while communicating via the cloud separating sensor nodes from the environment.

Pattnaik and Sahu created the EHO-Greedy algorithm and fuzzy grouping methodology to be combined for well-organized routing in WSN (Pattnaik and Sahu 2020). In this research, the EHO Greedy approach was applied, and a fuzzy-based cluster formation technique for efficient WSN routing was created. When employing extended EM, nodes at first appear in several clusters. It is hard for compactly dispersed diverse WSN CHs or BSs to manage such enormous quantities of information using the suggested approach, particularly in normal form. Additionally, information transmission to the WSN BS was slow.

Moharamkhani et al. (Moharamkhani et al. 2021) proposed a multi-objective fuzzy knowledge-assisted bacterial foraging optimizer to minimize traffic congestion. This paper presents moFIS-BFO, a hybrid approach based on the BFO and moFIS protocols for energy-efficient gathering in WSNs. Precedence in providing to control congestion, regulate gender in CHs, and stop extreme packaging remains. Consequently, the moFIS-BFO algorithm is inadequate for WSN of a wide scale (above 200 m).

The opportunistic routing technique for WSNs was developed by Ben Fradj et al. (Ben Fradj et al. 2018). This paper suggests the EEOR-FL protocol as a special "OR" protocol for use in WSNs. In WSNs, nodes must balance and minimise their power use, this study presents a new opportunistic routing technique. The technology successfully equilibria energy usage and lengthens the lifespan of the networks, according to simulation results.

A helpful fuzzy-based continuous node refinement technique was presented by Elavarasan and Chitra (Elavarasan and Chitra 2020) based on the multilayer routing architecture of WSNs. The major aim is to provide a multi-layer protected communication channel for WSNs. Tracking the SN's position and observing its actions are the goals. To study its behaviour, the F-CNR approach was created. The programme finds nodes that are not appropriate for communication and eliminates them. Every intermediate node in the routing chain is under the control of the sending node.

A novel CH selection technique for the LEACH technique for WSNs was created by Al-Baz and El-Sayed (Al-Baz and El-Sayed 2017). The LEACH is an energy-adaptive, hierarchical process that lengthens the life of the current network. The cluster head rotation method uses LEACH to guard against unplanned node failures.

Rajakumar et al. (Rajakumar et al. 2021) established an energy-efficient group generation in a WSN using grey wolf optimization (GWO). For this project, the GWO method was employed to select energy-efficient CHs. Due to its strong leadership qualities and hunting techniques, this algorithm appeals to many academics; nevertheless, because of its weaknesses in exploitation and exploration, it produces subpar cluster formation in WSNs when utilised. The WSN problem will be solved by the recommended technique, which comprises a tuning factor for effective exploitation and exploration. The experiment findings show that the suggested technique produces superior results.

For wireless mesh networks, Rozner et al. (Rozner et al. 2009) created a straightforward opportunistic adaptive routing (SOAR) system. This article proposes the use of SOAR to explicitly enable many concurrent movements in a wireless mesh network. The research is conducted on an A18-node wireless mesh test-bed, and the results demonstrate that SOAR considerably beats conventional routing and ExOR, a pioneering opportunistic routing algorithm, in a variety of circumstances. Ramalingam et al. presented the efficient data transfer for several usage of the Blynk IoT server (Ramalingam et al. 2019). For real-time applications, a smart Internet of things device is developed using Bluetooth Low Energy and WSNs. The data was collected using a smart IoT device and sent to the cloud (Aravinth et al. 2013).

The cluster-tree-inspired energy-saving data collection strategy for factory automation employing WSNs and IoT was developed by Karunanithy and Velusamy (Karunanithy and Velusamy 2020). The CTEEDG protocol was introduced in the study to extend the life and output of WSNs. Based on the localized data, the CTEEDG chooses the group head (CH) using fuzzy logic. Throughout the intercluster transmission phase, a "tree topology" is constructed among the clusters to ensure the availability of the shortest, least congested route to the BS. The simulation results showed that the proposed CTEEDG outperformed FAMACROW and DLLEACH in terms of throughput by 28.81% and 38.18%, respectively.

EEOR-FL is a novel opportunistic routing method that Fradj et al. (Fradj et al. 2018) described. They utilised a similar fundamental idea as the EEOR procedure but additionally utilised a novel approach to reducing energy usage and selecting the list of candidates for the aim. An opportunistic routing system called EEOR-FL is based on EEOR and employs a novel way to choose the list of candidates. A frame delivered in broadcast mode when a root wants to send data to its goal may be received by any node in the neighbourhood. Following the sequence specified by the list of the frame's header, each recipient of the framework sends an acknowledgement to the source. The source can compute the costs and compile a list of contestants who will best progress the frame to its destination by getting these acknowledgements.

Del-Valle-Soto, et al. (Del-Valle-Soto et al. 2023) conducted a study on WSN in their research. They employed an optimization algorithm for analysis and made useful findings that enriched the field. In their latest work, Roberts and Thangavel (Roberts and Thangavel 2022) have created an energy-aware multipath routing protocol that is specifically designed for IoT-based WSNs and is well-optimized using ticket managers. They present new ideas for the study of enhancing the efficiency of the network. To improve the performance of the network, Joshi, P., et al. (Joshi et al. 2023) reported a novel method that combines routing and clustering in WSNs. They use a specific tack while tackling the problems brought on by diverse surroundings. A novel energy-efficient DA technique with superior performance over earlier approaches was developed by Roberts et al. (Kingston Roberts and Thangavel 2023). Their research focused mainly on using secure clustering and routing to increase the reliability and security of wireless sensor networks. As a result, our work adds significantly to the body of knowledge already available on improving network security and resilience.

Sperm Swarm Optimization (SSO), a novel meta-heuristic optimization technique based on the process of sperm fertilization, is presented by the authors in their work (Shehadeh et al. 2018). Within SSO, the swarm starts from an area with low temperature called the Cervix and proceeds towards an area with high temperature referred to as the Fallopian Tubes to obtain the best solution. It has been demonstrated that SSO may be applied to a variety of WSN issues to reduce latency and end-to-end delays while maximizing packet throughput or energy consumption.

The authors of the study (Shehadeh 2021) presented the Hybrid Sperm Swarm Optimization with a Gravitational Search Algorithm (HSSOGSA), which integrates the application of a Gravitational Search Algorithm (GSA) with the investigation of Sperm Swarm Optimization (SSO). Using the CEC 2017 benchmark suite, algorithm performance is evaluated and compared to the fundamental GSA and SSO in terms of both qualitative and quantitative features. Results show that HSSOGSA performs better in escaping local optima and achieves faster convergence across various benchmark functions.

The Chernobyl Disaster Optimizer (CDO), a novel metaheuristic optimization method based on the nuclear reactor disaster at Chernobyl, is presented by the authors in their work (Shehadeh 2023). CDO resembles radiation in the same manner that gamma, beta, and alpha particles are released from high-pressure to low-pressure. The created algorithm's performance is evaluated using the Congress on Evolutionary Computation (CEC 2017) benchmark and contrasted with the capabilities of currently available methods, including the Gravitational Search Algorithm and Sperm Swarm Optimization. From the above results, it can be concluded that CDO is an efficient and competitive optimization method.

In their recent study (Jaiswal and Anand 2021), Authors proposed a new method to improve the clustering process in WSNs for improving the QoS of IoT applications. Their method is based on the GWO and its main goal is to enhance the performance of the WSNs. The GWO technique has the following benefits when it comes to exploration and exploitation. However, it should be noted that factors like convergence speed and parameter choices might affect how well the algorithm performs. In their work (Reddy et al. 2021), the authors proposed a new method that integrates glowworm swarm optimization with ACO to improve the energy utilization of clustering and routing in WSNs. This combination of algorithms integrates the strengths of both, but it also has issues with the tuning of parameters and convergence. ISSA was employed by Qaffas, Alaa A (Qaffas 2023). to solve the issues of grouping and low-energy routing in WSNs. The ISSA offers a different perspective by mimicking the behaviour of a squirrel that forages for food and could offer good solutions to clustering and routing challenges. Nonetheless, its efficiency may be rather contingent on things such as which parameters are selected and when the algorithm is solved.

2.1 Research Gaps

The state of meta-heuristic cluster head algorithms for WSNs in the current literature shows the following research gaps that the proposed method seeks to fill. One of the major issues relates to the lack of effective algorithms for the selection of the cluster heads that would help prolong the WSNs' lifespan and at the same time conserve energy. Original clustering algorithms such as LEACH rely on decentralized probabilistic techniques for the selection of CHs; however, they are not very effective when it comes to non-uniform node distribution and energy consumption optimization. To address these issues, existing algorithms such as DSBCA and PSO-C incorporate node density, residual energy, and distance, among other characteristics. Still, these methods can be limited by load balancing, energy distribution, and computational efficiency. Further, approaches like nCRO and PSO-ECHS are also dedicated to the enhancement of network lifespan; however, they may not efficiently distribute the energy load among CHs or regulate the equal formation of the clusters. A second research gap can be identified in the area of fine-tuning routing protocols according to the characteristics of a given network environment, e.g., WSNs with mobile sinks, and big and congested IoT networks. Though techniques like TCBDGA and FRLDG-based solutions provide new strategies for data collection and cluster formation, they may not be scalable or may not cover problems related to congestion and delay. In addition, there is a requirement for the development of algorithms that combine several optimization procedures to obtain high effectiveness in various network characteristics. Although methods such as EEOR-FL and EHO-Greedy use fuzzy logic, firefly algorithms, or bacterial foraging optimization, they may have issues with scalability, convergence rate, or computation time.

The proposed grouping and Energy Efficient Routing Protocol which is called Enhanced Squirrel Search Algorithm-based goals fill these gaps in the existing research by providing a solution that incorporates the features of adaptive population initialization, dynamic step size control, and local search algorithms. to accelerate the rate of convergence, this strategy seeks to boost SSA exploration and exploitation, enhance the quality of the solution and lower energy use in WSNs.

3 Squirrel search algorithm

Soaring across great distances by glide, a successful strategy used by small animals, SSA mimics the active feeding actions taken by FSs in the south found in the woods of Europe and Asia. In warm weather, gnawing creatures glide from one tree to another in search of food sources. Acorn nuts are easily obtained by them to meet their daily energy demands. Hickory nuts are squirrels' favourite wintertime food source, therefore they start looking for these. In the winter, they become less active and rely on hickory nuts to satisfy their energy needs. With rising temperatures comes an upsurge in FS activity. The SSA is based on the previously described process, which recurs and continues during the squirrels' whole existence. According to the FSs' method of locating food, the optimisation SSA may be represented by the subsequent mathematical phases.

Assume that there are FSs in a forest of deciduous trees and that each squirrel is perched on a sole tree. Every FS is resourceful and uses its resources to its full potential while foraging for food available by acting dynamically. In woods, there are only three kinds of trees.: common trees, hickory trees (which yield hickory nuts for food), and oak trees (which give acorn nuts for food). In the wooded area under examination, there is a putative standing among three oaks and a single hickory.

In the same vein as previous algorithms that use demographic data, FSs are started in an arbitrary location by SSA. In a d-dimensional lookup space, the position of an FS is represented by a vector. Consequently, the FSs can glide throughout a multi-dimensional lookup space while adjusting their location vectors.

3.1 Random initialization

As mentioned before, there are several FS in FSs, and each one's position may be determined using a vector. The distribution of every FS may be seen in the following matrix:

$$FS = \begin{bmatrix} FS_{1,1} & \cdots & FS_{1,d} \\ \vdots & \ddots & \vdots \\ FS_{n,1} & \cdots & FS_{n,d} \end{bmatrix} \tag{1}$$

where $U(0,\ 1)$ is an arbitrarily distributed varied in the range [0, 1], and FSL and FSU denote, correspondingly, the ith FS's upper and lower boundaries in the jth idea.

$$FSi\ =\ FSL\ +\ U(0,\ 1)\ \times\ (FSU\ -\ FSL) \tag{2}$$

Where $FS_{i,j}$ denotes the j^{th} dimension of the i^{th} FS. Equation 2 states that the starting locations of each FS are spread equally.

3.2 Fitness calculation

To find the position fitness for each FS, the values of the choice variation, also known as the solution vector, are input into a fitness function that has been established. Next, the output values are kept in the given array.:

$$f = \begin{bmatrix} f_1\left([FS_{1,1},\ FS_{1,2}, \ldots\ , FS_{1,d}]\right) \\ f_2\left([FS_{2,1},\ FS_{2,2}, \ldots\ , FS_{2,d}]\right) \\ \vdots \\ \vdots \\ f_1\left([FS_{n,1},\ FS_{n,2}, \ldots\ , FS_{n,d}]\right) \end{bmatrix} \tag{3}$$

Each FS's preferred food source is determined by the position's fitness score; for example, the ideal food source is a hickory tree, whereas the typical food source is an acorn tree, or there is no food source at all (an FS on a regular tree). Additionally, this data shows the FS's chances of survival.

3.3 Randomized sorting and selection

When each FS's position values are logged for fitness, the array is arranged in ascending. There have been reports of an FS with poor health value on the hickory tree. The next three best FS are expected to migrate to hickory trees, which are believed to be on acorn trees. The FSs that make it are predicted to reside on common trees. It is anticipated that, more haphazardly, when they run out of daily energy, some squirrels may follow the path of the hickory nut tree. The surviving squirrels go to visit acorn trees (to fulfil their daily need for energy). The FS's hunting strategy is continually impacted by the presence of predators. In the case that a predator is present, this natural reaction is replicated using the position update mechanism.

3.4 Generate new locations

As formerly noted, when FS engage in dynamic foraging, three possibilities may occur. In these cases, it is thought that when there is no predator around, the FS walks about and thoroughly searches the forest for its preferred food; when there is, however, a predator there, it becomes cautious and must take a quick, haphazard stroll to find a hiding place close by. The dynamic foraging behaviour may be explained by the following model:

Case 1 From acorn nut trees, FSs may go in the direction of hickory nut trees (FSat). The new squirrel posture in this case may be found as follows:

$$FS_{at}^{t+1} = \begin{cases} FS_{at}^{t} + d_g \times G_c \times \left(FS_{ht}^{t} - FS_{at}^{t}\right) R_1 \geq P_{dp} \\ \quad Random\ Locatioon \qquad otherwise \end{cases} \tag{4}$$

where t is the current iteration, $R_1$is an arbitrary value that falls between $[0,\ 1]$, d_g is the random gliding distance, and FS_{ht}^{t} the location of the FS that was successful in acquiring the hickory tree where it was located. In the provided model, the glide constant G_c helps to provide stability between exploration and exploitation. Its worth most importantly affects the effectiveness of the provided algorithm. In the current study, G_c is valued at 1.9, which was established by closely examining.

Case 2 FSs on regular trees () may relocate close to acorn nut trees to fulfil their everyday vitality demand. In this instance, the following are new squirrel places that can be found:

$$FS_{nt}^{t+1} = \begin{cases} FS_{nt}^{t} + d_g \times G_c \times \left(FS_{at}^{t} - FS_{nt}^{t}\right) R_2 \geq P_{dp} \\ \quad Random\ Locatioon \qquad otherwise \end{cases} \tag{5}$$

where R_2 is any number inside the interval [0, 1].

Case 3 Some FSs on ordinary trees that have previously received acorn trees may move closer to hickory trees in the state to save hickory trees that can be used-up during a food crisis. In this case, new squirrel sites are found in the following ways:

$$FS_{nt}^{t+1} = \begin{cases} FS_{nt}^{t} + d_g \times G_c \times \left(FS_{ht}^{t} - FS_{nt}^{t}\right) R_3 \geq P_{dp} \\ \quad Random\ Locatioon \qquad otherwise \end{cases} \tag{6}$$

where R3 is a chance value between 0 and 1. In this particular research, the probability of the existence of a predator, denoted by the symbol P_{dp}, is constantly considered to be 0.1.

3.5 Seasonal condition monitoring

Seasonal variations have a major effect on FS behaviour while foraging. Their small size, high body temperature, and risky feeding owing to active predators allow them to miss a lot of thermal energy in cold weather. Climate causes make them less energetic in winter than they are in autumn. FS movement is influenced by weather fluctuations, therefore taking this behaviour into account might lead to a more precise optimisation strategy. Therefore, to forbid the approach from being cornered in the local optimal solution, SSA incorporates a seasonal monitoring state. The following stages are included in the behaviour's modelling:

a. Firstly, using Eq. (7), get the seasonal constant using the formula.

$$S_c^t = \sqrt{\sum\nolimits_{k=1}^{d} \left(FS_{at,k}^{t} - FS_{ht,k}\right)^2} \tag{7}$$

where $t = 1,\ 2,\ 3.$

b. Verify that the seasonal observing criterion $S_c^t\, S_{min}$, is met. The seasonal constant's smallest value, or S_{min}, is calculated as follows:

$$S_{min} = \frac{10E^{-6}}{(365)^{t/\left(\frac{tm}{2.5}\right)}} \tag{8}$$

where the iteration values t and tm, respectively, denote the current and maximum values. The parameter S_{min} affects the proposed approach's capacity for exploration and exploitation. While greater values of S_{min} stimulate exploration, small values of S_{min} enhance the algorithm's ability for development. For any metaheuristic to be effective, these two steps must be well-balanced. This equilibrium is maintained by the gliding constant G_c (Eqs. (4), (5), and (6)), it is possible to enhance it by adjusting the value in a flexible manner S_{min} throughout each iteration.

c. After the winter season has ended and the seasonal monitoring condition has been confirmed, FSs should be randomly moved if they are unable to search the forest for the most winter food available.

3.6 Random movement after the winter season

when was previously established, lower food costs cause FS activity to rise when winter ends. The FSs that made it through the winter but were ineffective at scouring the forest for a good food source could now diverge. Incorporating this tendency into the models might enhance the proposed algorithm's exploratory potential. Squirrels are only believed to have relocated in search of good food sources if they were incapable of finding food in the hickory nuts but still managed to live. The motion of these FSs is modelled by the following equation:

$$FS_{nt}^{new} = FS_L + Levy\,(n) \times\; (FS_U - FS_L) \tag{9}$$

where the Lévy supply encourages more extensive and efficient search space exploration. Scholars modify the total exploration capabilities of numerous metaheuristic procedures by using the potent numerical methodology of Lévy flight. Finding unique solutions that are far from the greatest choice currently available is made easier by using Lévy flights. For this specific type of random walk, the step length is found using a Lévy supply. One generalization that may be used to describe this distribution is the power-law equation. The following is the mathematical formula for the Lévy supply:

$$L\,(s, \gamma\,, \mu\,) = \left\{ \begin{array}{c} \sqrt{\frac{\gamma}{2\pi}} exp\left[-\frac{\gamma}{2(s-\mu\,)}\right] \frac{1}{(s-\mu\,)^{3/2}},\;\; 0 < \mu\; < s < \infty \\ 0,\;\; otherwise \end{array} \right. \tag{10}$$

in which , > 0. We have two parameters: for shift and for scaling. This is how the Lévy flight calculation is done.

$$Levy\,(x) = 0.01 \times \frac{r_a \times \sigma}{|r_b|^{\frac{1}{\beta}}} \tag{11}$$

When is a constant that is taken to be 1.5 in the current work, r_a and r_b are two arbitrarily dispensed variables in the interval $[0,\ 1]$. and are identified as:

$$\sigma = \left\{ \frac{\Gamma\,(1 + \beta\,) \times \,\sin\left(\frac{\pi\,\beta}{2}\right)}{\Gamma\,\left(\frac{1+\beta}{2}\right) \times \,\beta\, \times \,2^{\left(\frac{\beta\,-1}{2}\right)}} \right\}^{1/\beta} \tag{12}$$

and $\Gamma(x) = (x-1)!$

3.7 Stopping Criteria

A common convergence criterion is function tolerance, which defines a small yet reasonable threshold value between the two final solutions. On occasion, the maximum execution time may be one of the halting conditions. In the current study, the all-out number of iterations serves as the stopping point. The SSA pseudocode is given in Algorithm 1.

1. Define input criteria.
2. Generate initial positions for n FSs using Eq. (2).
3. Evaluate the fitness function for each FS's location.
4. Arrange FS locations in ascending order based on fitness.
5. Verify FS presence on various tree types such as acorn, hickory, and others.
6. Randomly relocate FSs from regular trees to nut trees (hickory); the rest move to nut trees (acorns).
7. ***While*** (Not meeting halting criteria):
   a. ***For*** $t\ =\ 1$ to n_1 (n_1 = Total FSs on acorn nut trees moving towards hickory trees):
      - ***If*** $R1\ \geq\ P_{dp}$, compute FS_{at}^{t+1} using Eq. (4).
      - ***Else***, set FS_{at}^{t+1} to a random location in the search space.

   b. ***For*** $t = 1$ to n_2 (n_2 = Entire FS population migrating towards acorn trees on common trees):
      - ***If*** $R2\ \geq\ P_{dp}$, compute FS_{nt}^{t+1} using Eq. (5).
      - ***Else***, set FS_{nt}^{t+1} to a random location in the search space.

   c. ***For*** $t = 1$ to n_3 (n_3 = FSs on other trees moving towards a hickory tree):
      - ***If*** $R3\ \geq\ P_{dp}$, compute FS_{nt}^{t+1} using Eq. (6).
      - ***Else***, set $FS_{nt}^{t+1}$to a random point in the search space.
8. Set seasonal constant (Sc).
   - ***If*** (the need for seasonal observation is satisfied), randomly move FSs using Equation (14).
9. Adjust the marginal value of the seasonal constant (S_{min}) using Eq. (13).
10. A hickory tree is the optimal location for the squirrel, and the optimum solution matches its position.
11. Conclusion.

Algorithm 1Pseudo code for SSA

4 Proposed clustering protocol

This section provides a detailed description of the recommended protocol. To put the provided SSA-C process, we have to make certain assumptions as follows: All nodes are fixed after they have been deployed. The nodes are uniform in their makeup. Additionally, the BS is immobile and has enough energy. After deployment, the nodes are left unattended.

CH selection and cluster formation are the first and second phases of the clustering process, respectively.

4.1 Improved squirrel search algorithm (I-SSA)

In the context of optimizing the SSA for WSN routing, the I-SSA incorporates several enhancements to expedite convergence and enhance solution quality. Specifically, we used Adaptive Population initialization, Dynamic step size control, and local search algorithm to enhance the exploration and exploitation capabilities of SSA.

4.1.1 Adaptive population initialization

The objective of Adaptive Population Initialization is to generate an initial population of solutions that are well-suited to the problem space, taking into account factors such as network topology and sensor node distribution. This attempts to decrease convergence time and increase algorithm efficiency by beginning near possible optimum solutions.

Let WSN be the wireless sensor network with sensor nodes; the problem is to create an initial population of solutions for routing in the network. Every solution in the population is a potential layout of routes for data interconnection of the sensor nodes. The objective is to ensure the initial population has features similar to the network topology and distribution of sensor nodes to enhance convergence towards the best routing solutions.

The following elements are crucial to the defining of the issue and the solutions in the context of routing optimization for wireless sensor networks. These variables include the initial population of solutions denoted as P, where each solution x_i is a candidate routing configuration of the sensor nodes. N is the number of sensor nodes in the network, and $f\left(x_i\right)$ is the fitness function used to assess the quality of a particular solution. Also, the problem depends on the topology matrix T which defines the connection between the sensor nodes and the distribution matrix D which illustrates the placement of the nodes. Constraints specify that each member in the population must contain a connectivity defined by the topology matrix, T, and a spatial distribution defined by D, in addition to the population size $\mid P \mid$, which must be large enough to contain a good number of possible routing schemes. In mathematical terms, the Adaptive Population Initialization process is described in the function $AdaptiveInit\left(\right)$, which creates the initial population P using the topology matrix T and distribution matrix D. This function employs information from the matrices to create solutions that fit the problem space. Measures like proximity-based route assignment and connectivity patterns are used to achieve the right distribution of resources. When algorithmic implementation is to be carried out, the API process is incorporated within the overall routing optimization algorithm like the SSA. During the initialization stage, The initial population P, which serves as the foundation for the ensuing routing configuration optimization, is created by calling the $AdaptiveInit\left(\right)$ method. It is possible to incorporate adaptive mechanisms into $AdaptiveInit\left(\right)$ to influence the population generation based on the changes in the network or the problem at hand.

The strength of the Adaptive Population Initialization can only be determined if its results have a positive effect on convergence time and the quality of the solutions. It is possible to compare various aspects of the algorithm's performance with and without adaptive initialization by comparing the results of specific scenarios, including convergence speed, stability of the method and the quality of the resultant solution. The simulation of WSN in a real-world environment in various situations helps to determine the feasibility and advantages of the adaptive population initialization for the routing problem.

4.1.2 Dynamic step size control

Dynamic Step Size Control is important in the optimization process since it helps in changing the step size or mutation rate during the optimization process. The goal of this adaptive mechanism is to strike a balance between the search space's exploration and exploitation, this is essential to finding the best solution by efficiently navigating the region and taking advantage of the places that show promise. In mathematical terms, the step size or mutation rate is represented by, ' μ ', and the dynamic control of this step size is done by the function $DynamicStepControl\left(\right)$. This function is intended to change the step size or mutation rate depending on some parameters such as the fitness, the degree of convergence, and the exploration versus exploitation. In general, the dynamic step control function can be described as follows:

$$\mu = DynamicStepControl\left(\right) \tag{13}$$

Where μ represents the adjusted step size or mutation rate.

4.1.3 Local search mechanism

The Local Search Mechanism is used as a component in optimization algorithms and it contains a method to use encouraging areas in the search space. This mechanism increases the algorithm's ability to provide local improvements to solutions that are fine-tuned. One commonly employed technique within local search is hill climbing, where small perturbations are applied to the current solution to iteratively enhance its fitness within the immediate vicinity. Mathematically, the local search operator is denoted as $LocalSearch\left(\right)$, and it operates on the current solution x. The function $LocalSearch\left(\right)$ perturbs x to generate a new solution $x\prime$, whose fitness is subsequently evaluated. If $x\prime$ demonstrates superior fitness compared to x, it replaces x. This functioning can be indicated as:

$$x\prime = LocalSearch\left(x\right) \tag{14}$$

Where $x\prime$ represents the new solution obtained through local search.

4.2 Cluster head (CH) selection

The ISSA approach is used to choose CHs in a network. In general, the CHs are chosen based on WSN measurements for example residual energy, degree, and distance. In suggested ISSA-C procedure,, to choose the CHs, a new option called the CH balance factor is offered. Following network activation, all SNs report their precise position and leftover energy to BS. The ISSA-C technique is used by the BS. Based on parameters including intra-cluster distance, sink distance, residual energy, and the CH balancing factor, a fitness function is being constructed.

Electing the CHs in the networks to increase their tenure is the main objective of the ISSA-C. When choosing CHs, four factors are taken into consideration. The mean intra-cluster space, the average space between CHs, the average residual energy, the average distance between sinks, and the CHs is variables are the factors that balance out. The part that follows covers the terminology used in the proposed protocol, and the section that follows defines the fitness function utilised in the suggested protocol.

From the top 5% of the active sensor nodes with residual energies that are greater than the mean residual energies, one CH is chosen by every pack. The fitness function is then determined for every CH in the packs. As the last and new CH, the node in the pack with the lowermost fitness function value is chosen. The terms used to execute the ISSA-C protocol are given in Table 1:

4.3 Formulation of the fitness function

A key factor in determining the efficacy and efficiency of network functioning in wireless sensor networks is the fitness function that is employed for CH selection. The formulation of the fitness function incorporates several factors, each contributing to different aspects of network performance and energy efficiency. These factors are carefully chosen to address specific concerns related to energy usage, intra-cluster communication, distance to sink nodes and cluster size balance. The factors listed below are used to determine how the fitness function is calculated:

4.3.1 Residual energy (f1)

Because the network's lifetime depends on how energy is used, it is imperative to limit energy use. As an outcome, this factor is well thought out. It is determined as the summation of all the chosen CHs' current energy. Since the overall amount of energy essentially is maximised, taking into consideration the reciprocal of this ensures that each goal function is in a state of complete equilibrium.

To prolong the network's life, sensor nodes' residual energy levels must be monitored and managed, as these nodes consume energy during data transmission and processing. Through

Table 1 Terms used in the ISSA protocol

n	The overall number of live SNs
m	The overall number of CHs
CH	The set of all the cluster heads (CHs), $CH = (CH1, CH2, CH3, \ldots, CHm\}$
SN	The set of all SNs, $SN = \{SN1, SN2, SN3, \ldots, SNn\}$
l_j	No. of SNs in the cluster j
T_H	Threshold energy for the existence of a CH
$D_{\text{CHj-BS}}$	Distance between CH CHj and BS
$R_{\max}$	Max transmission range of CH
$D_{\text{sk-CHj}}$	Distance amid sk and CHj
$D_{\text{sk-sj}}$	Distance amid two SNs sk and sj
$D_{\max}$	Range of the SN
C_{sk}	Every SN within the transmission range
E_{CHj}	CH's current energy CHj, $1 \leq j \leq m$
E_{sk}	SN's sk preliminary energy, $1 \leq k \leq n$

the incorporation of each CH's residual energy into the fitness function, the algorithm seeks to identify CHs that collectively optimize energy utilization throughout the network. The equation for calculating the reciprocal of the summation of energies of all selected CHs is f1. The reciprocal mentioned here ensures that the health function is optimised by minimising the overall energy consumption of the selected CHs. This aligns perfectly to achieve energy efficiency.

$$f_1 = \frac{1}{\sum_{j=1}^{m}(E_{CHj})} \tag{15}$$

4.3.2 Average intra-cluster distance (f2)

The intra-cluster distance is the total distance between each sensor node and the associated CH. If the network is to use as little energy as possible, lowering this intra-cluster distance is necessary.

To minimize the distances between sensor nodes and their corresponding CHs within the same cluster, the average intra-cluster distance factor, or f2, is used. Sensor nodes in WSNs send their acquired data to their corresponding CHs, which then transport the combined data to the base station or sink node. The algorithm aims to minimize energy usage by decreasing the distances of communication in the cluster. The mathematical representation of the equation that is used to determine the sum of distances of each sensor node to its respective CH multiplied by the data packet length is given by -2 f2. This weighting also considers the energy which is utilized in data transfer; thereby ensuring that the fitness function provides a higher preference to shorter distances.

Because SNs use an amount of energy while communicating with their respective CHs, it is presented as:

$$f_2 = \sum_{j=1}^{m}\left(\frac{1}{lj}D_{sk-CHj}\right) \tag{16}$$

4.3.3 Average sink distance (f3)

The number of SNs linked to the CH divided by the CH's distance from the BS and the CH yields the average sink distance. This statistic is considered because distance is such a vital parameter of energy consumption. Therefore, the distance between the two points has to be brought down to reduce energy usage.

The distances of CHs to the network's sink node or base station are taken into account by the sink distance factor, represented by the symbol f3. As data packets move from CHs to the sink node, it is observed that the coverage over a larger distance increases the energy expenditure due to increased transmission costs. Minimizing these distances is useful for energy-saving and increasing the network's lifespan. The equation that defines the sum of the distances between each CH and the sink node with the data packet length as a factor is f3. The weighting in the fitness function encourages energy-conservative routing by giving preference to smaller distances to the sink node.

$$f_3 = \sum\nolimits_{j=1}^{m} \left(\frac{1}{lj} D_{CHj-BS} \right) \tag{17}$$

4.3.4 CH balance factor (f4)

There needs to be some sort of balance in the cluster's size since the more companies there are inside the cluster, the more, the more competition there will be between them. This kind of deployment of the sensor nodes means that there can be both large and small clusters. Therefore, to address energy utilization, this factor is considered.

The CH balance factor, f4, strengthens the importance of the balanced sizes of clusters in the network. Unequal cluster sizes lead to energy dissipation inequality in the sense that some CHs are burdened with a larger amount of data and thus, consume more energy than others. The method considers the average cluster size and the variance in the number of sensor nodes in each cluster to spread the energy burden across the network in an equitable manner. f4 is the equation that is used to compute the difference and include it in the fitness function. The algorithm aims to minimise the difference, selecting CHs that help achieve more balanced cluster sizes. This promotes energy efficiency and enhances network stability.

$$f_4 = \sum\nolimits_{j=1}^{m} \frac{n}{m} - l_j \tag{18}$$

It employs the subsequent fitness function:

$$\mathrm{F} = \mathrm{a}^*\mathrm{f1} + \mathrm{b}^*\mathrm{f2} + \mathrm{c}^*\mathrm{f3} + (1 - \mathrm{a} + \mathrm{b} + \mathrm{c})^*\mathrm{f4}, \tag{19}$$

where a, b, and c are constant values and a+b+c=1.

Rather than separately minimising each fitness function, it is preferable to minimise the merged health functions of the four components, which were described before, as shown in Eq. (17). The fitness indicators stated above complement one another well.

4.4 Energy model

In such a paradigm, the offset distance (d_0) is larger than the transmitting distance (d), and the SN's energy uses is precisely proportionate to d_2. The following equations express the total energy consumed by each node to convey a l-bit data packet:

$$E_{TX}(l, d) = \left\{ \begin{array}{l} l \times E_{elec} + l \times \epsilon_{fs} \times d^2, \ ifd < d_0 \\ l \times E_{elec} + l \times \epsilon_{mp} \times d^4, \ ifd \geq d_0 \end{array} \right\} \tag{20}$$

where mp is used in the multiple paths architecture, d_0 is the offset distance, fs stands for the energy required for enlargement, and E_{TX} is the total amount of energy required for communication. E_{elec} corresponds to the amount of energy that is required to run a circuit, like a receiver or transmitter, for each bit that is contained inside the framework of free space.

In contrast, the recipient circuit's energy consumption for retrieving l-bits of data is provided by

$$E_{RX}\,(1) = l * E_{elec} \tag{21}$$

These quantities rely on several variables, such as signal propagation, digital coding, modulation, and filtering. E_{elec} is the amount of energy required to complete one chunk of the journey, i.e., receiver or transmitter, and E_{RX} is the quantity of energy uses required to acquire data. It is difficult to model the entire propagation of radio waves since it is so changeable.

$$Etotal\ = E\ _{TX} + E_{RX}, \tag{22}$$

where $Etotal$ is the system's total energy loss.

The following is the algorithm and block diagram for the proposed ISSA-C protocol as shown in Fig. 1:

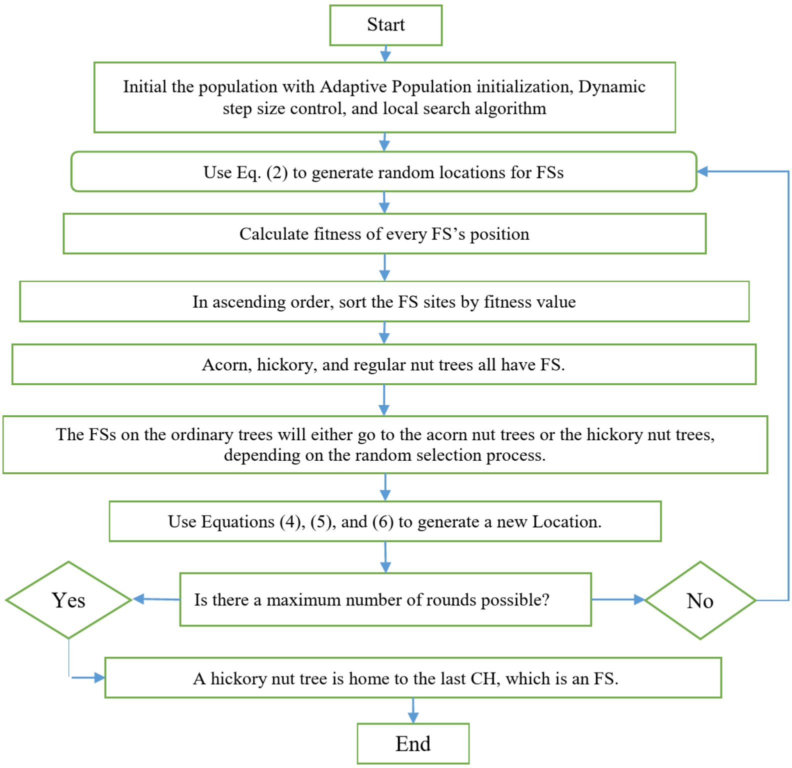

Fig. 1 Block diagram of the Proposed ISSA-C protocol

Input:
Group of alive SNs in a round,
No. of Packs Np
No. of CHs in a pack: 5 per cent of all active SNs whose residual energy exceeds the mean residual energy
Output: Best selection of $CH = \{CH_1, CH_2, CH_3, \ldots, CH_m\}$
pack initialization Pick 5% of the locAlive SNs where residual energy is higher than the average to serve as CHs.
/* choosing particular SNs to serve as CHs */
for i = 1 to Np do
Begin:
Specify the requirements for input
To generate random places for n FS, use Equation (2).
Determine the value of the fitness function for each FS's position.
Sort the FS locales into ascending order based on their fitness ratings.
Verify if FSs are present on acorn, hickory, and other tree species.
The FSs on normal trees that are assigned to hickory trees will be chosen at random, and the remaining FSs will be assigned to acorn nut trees.
While *(The requirement for halting is not satisfied)*
For *t = 1 to n1 (n1 = whole FSs those are on acorn nut and gliding to hickory tree)*
if *R1 ≥ Pdp*
Compute FS_{at}^{t+1} *by using the equation (4)*
else
FS_{at}^{t+1}= arbitrary place in the search area
end if
end
For *t = 1 to n2 (n2 = several FSs are heading toward acorn trees from regular trees.)*
if *R2 ≥ Pdp*
Compute FS_{nt}^{t+1} *by using the equation (5)*
else
FS_{nt}^{t+1} = a random position of search space
end if
end
For *t = 1 to n3 (n3 = A large number of FSs are going forward towards a hickory nut tree from other types of trees.)*
if *R3 ≥ Pdp*
Compute FS_{nt}^{t+1} *by using the equation (6)*
else
FS_{nt}^{t+1}= a random location of search space
end if
end
Calculate the seasonal constant (Sc)
if *(Seasonal monitoring requirements are satisfied.)*
Utilise Equation (14) to shift the FSs at random.
end if
Modify the minimum value (S_{min}) of the seasonal constant using Equation (13).
end
The last best option is to place the FS on a hickory nut tree that is selected as the Cluster Head (CH).
End

Algorithm 2Proposed ISSA-C

4.5 Energy-efficient opportunistic routing (EEOR)

Routing procedures need to be examined to determine the approach's efficacy and dependability. The routing phases are given as:

Step 1: Every SN sends data on the links' quality regularly.

Step 2: Based on this knowledge, an SN calculates the particular route and sends a list of transmitting SNs.

Step 3: It then directs this information in the form of a data packet.

Step 4: The transfer list SNs show a transfer timer and store the packets.

Step 5: The SN with the smallest timeout and the nearest to the endpoint sends the packet first.

Step 6: The other SNs will eliminate the pertinent packet from its queues to prevent repeated broadcasts.

The number of sink nodes and SN are both important aspects of network energy efficiency in WSN (base stations). In sink nodes, secure and removable sinks are offered. Every node in the cluster sends communications to CH. The sender is now CH, while the recipient SN are sink nodes. As a result, the path between the transmitter and receiver must have minimal power, delay, and traffic. It is crucial to select the quickest path possible while sending messages. The routing plan causes the quickest path to be picked since it also offers other potential connections. The identification of the shortest path and link quality are two crucial responsibilities in routing algorithms. To solve these two problems, an EEOR protocol technique is suggested. When EEOR is utilised to address connection issues in routing areas, the time complexity is significantly decreased.

As networks get bigger, the quantity of data they collect requires more energy, which leads to nodes shutting down early. To prolong the life of the network, many energy-saving procedures have been developed to decrease the quantity of energy used for data collection and sampling. The EEOR protocol aims to lower network energy usage, however it ignores packet delays and residual energy balance. This protocol optimises candidate selection and prioritisation algorithms to save energy. Additionally, the transmission power may be changed via EEOR. The number of candidates in the area will increase as the transmission energy gradually rises till the maximum threshold is reached.

The transmitter will thus add more nodes to the sequence to accommodate various transmit power levels. The sender chooses the available SN with the least amount of energy consumption from a list of SN that are prioritized by energy cost. EEOR has a smaller routing list size and needs less time to transmit data than the current protocol. EEOR uses less energy overall than the current approach. EEOR performs better than other current protocols when contrasting end-to-end latency methods and packet loss rates.

5 Result and discussion

This phase of testing and simulation is required in the simulation process since it aids in regulating the simulation's behaviour and guarantees that it is correct. The boundary's condition and beginning conditions are defined by the simulation settings, and the values of the model that control the running of the simulation. The state variables at the beginning of the simulation define the state of the system at any given moment. Such parameters are the network topology, nodes' energy status, and the positions of the sensor nodes. This may be achieved by specifying the initial conditions, which will allow the simulation to begin from a known state and lower the uncertainty of the simulation's results. The constraints that the simulation must follow are highlighted by the boundary conditions. Among the requirements taken into account are the network's maximum number of nodes, maximum energy levels of nodes and their maximum transmission power. The simulation may also be conducted in a realistic environment by setting up the boundary conditions and thus improving the realism and accuracy of the simulation outcomes.

To achieve the goal of the simulation, the following I-SSA parameters are crucial. Some of the factors include the population size, search space, energy consumption, and the quantity of repetitions. To evaluate the effectiveness of the suggested hybrid method, several simulations were carried out using Matlab 2021b on a PC with 8GB RAM, an Intel Core i7 CPU at 3. 9 GHz, and a Windows 10 operating system. Matlab should be used when simulating wireless sensor networks because it offers numerous tools and functions that enable the creation and execution of complex algorithms. The hardware component of the computer is also well-equipped to ensure that the simulations run efficiently and to the necessary standard to deliver accurate and consistent results.

The simulation parameters are shown in Table 2.

Performance of the suggested technique is assessed against that of the available clustering methods and routing procedures in the literature i.e., GWO (Mirjalili et al. 2014), SSA (Jain et al. 2019a, b), CDO (Shehadeh 2023), SSO (Shehadeh et al. 2018), MOCRAW (Chaurasia et al. 2023), EEWC (Pal et al. 2020), and MAP-ACO (Seyyedabbasi and Kiani 2020). The Throughput, PDR, BER, system lifespan, energy consumption, E2ED, buffer occupancy, and performance characteristics are computed utilising 1000 SNs and compared to other current approaches. In these simulations, a 1000 m2 area has 50 identical SNs and five cluster head nodes with unbounded battery energy.

The network's performance was simulated in terms of the PDR using the data collection approach that was given, latency, throughput, total energy and speed. The correlation between the network's performance (PDR, throughput, overall energy use, and latency) and the number of mounted SNs is shown in Figs. 2, 3, 4, 5, 6, 7, 8, 9 and 10.

5.1 Packet delivery ratio (PDR)

PDR determines the ratio between the packs provided by the sender and the packs received by the recipient. Figure 2 displays the PDR evaluation of both proposed and existing techniques. The diagram illustrates how the recommended system is more advanced than other designs.

The proposed ISSA-C method obtains a high PDR (88%) when measured against other systems. The PDR will increase when there are more SN growths. The PDRs of the GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO techniques are separately 85%, 85.5%, 85%, 85.5%, 86%, 86.5, and 87%.

5.2 Throughput

The quantity of received packets at the receiver divided by the duration required for a packet to be transmitted, is known as Throughput. The throughput evaluation of the suggested pro-

Table 2 Simulation parameters

Parameter	Value
Space	1000*1000 m2
No. of SNs	50 to 1000
Percentage of CHs	5%
No. of Search Iterations	5
No. of Rounds (Rmax)	1000
Data packet length (l) (bits)	4096
The energy of each SN	0.5 J

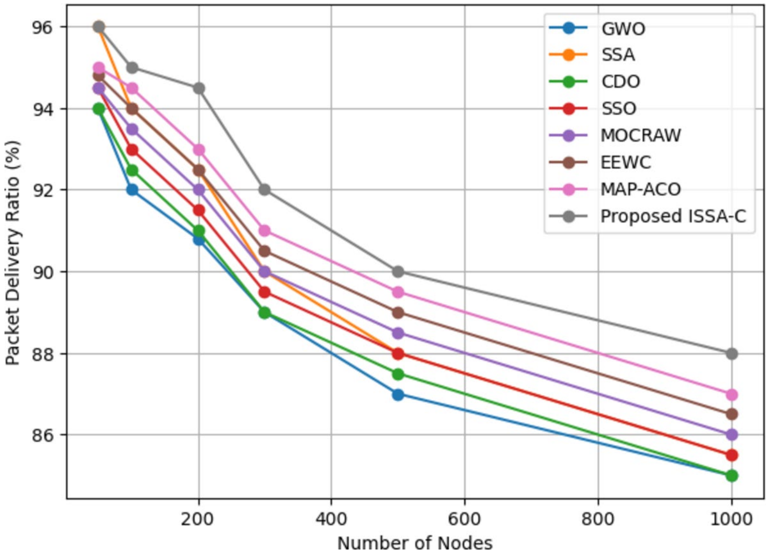

Fig. 2 Number of SNs versus PDR

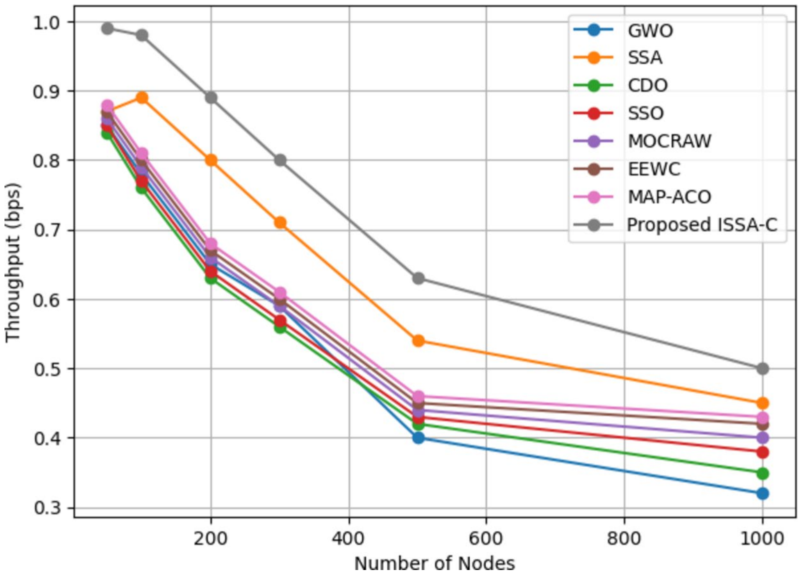

Fig. 3 Number of nodes versus Throughput

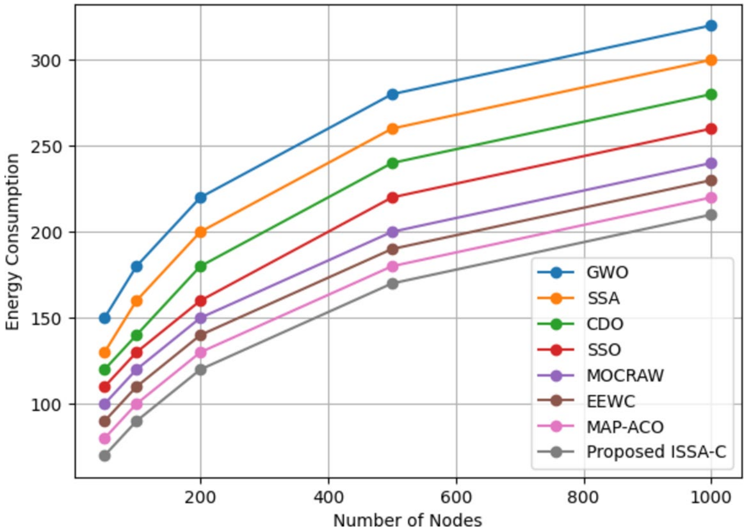

Fig. 4 Number of SNs versus Energy Consumption

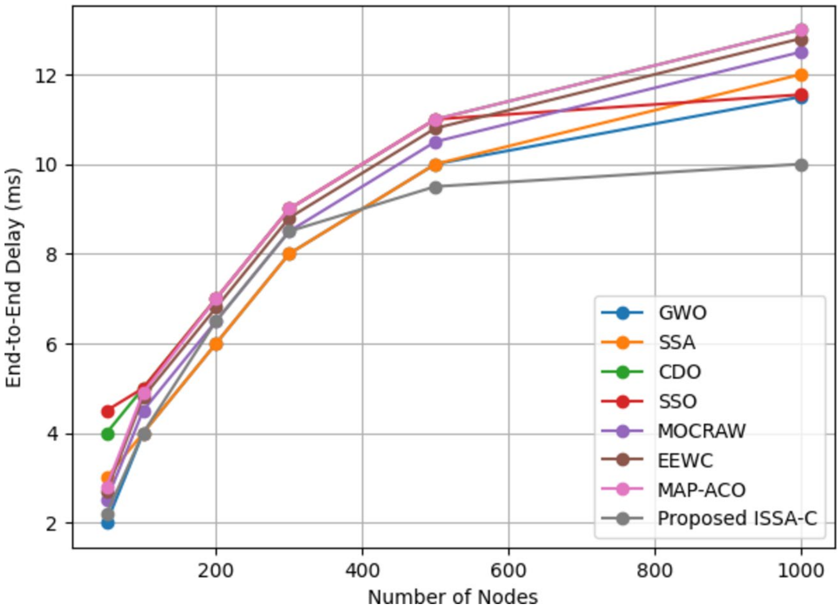

Fig. 5 Number of SNs versus E2ED

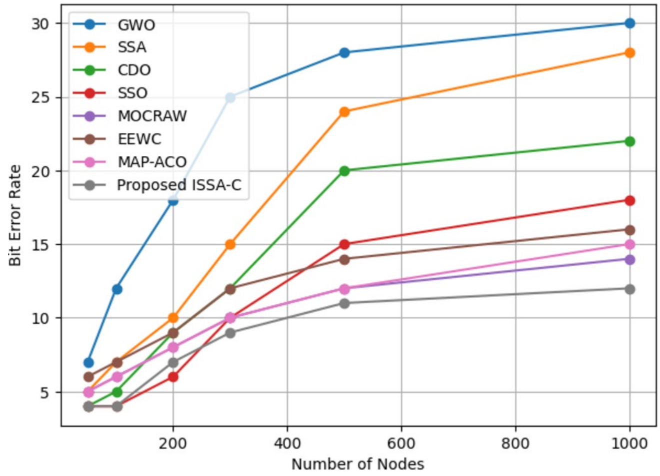

Fig. 6 Number of SNs versus BER

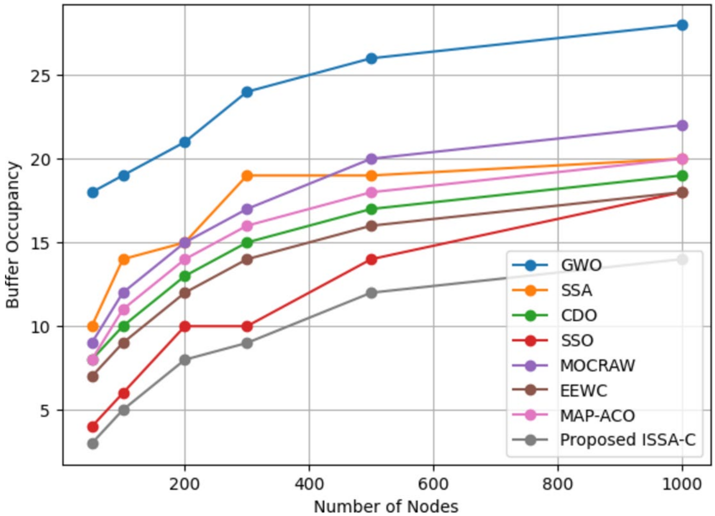

Fig. 7 Number of SNs versus Buffer Occupancy

tocol and the methods available in the literature is shown in Fig. 3. The graphic unequivocally demonstrates how the expressiveness of the suggested protocol has improved.

5.3 Energy consumption

The total amount of received energy, transmitted energy, and node count is referred to as energy consumption. Figure 4 compares the overall energy consumption of the proposed plan to various current plans. The developed protocol consumed less energy (210 mJ) in 1000 nodes than other current methods. The graph above demonstrates how, in compari-

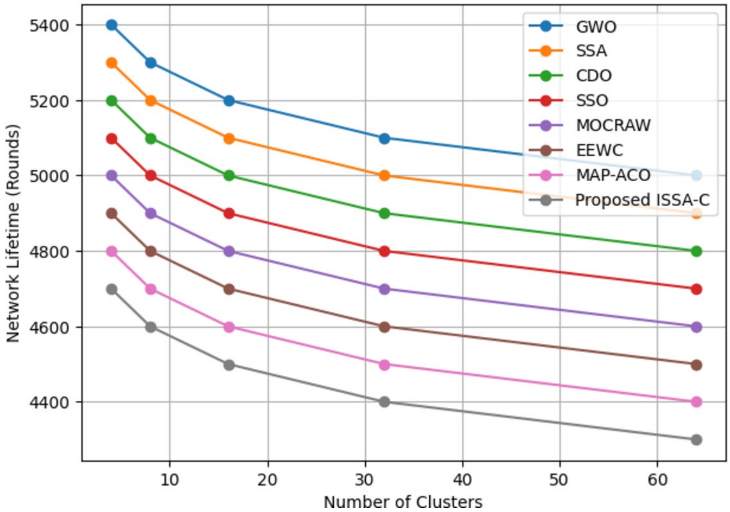

Fig. 8 Number of Clusters versus Evaluation of Network Lifetime

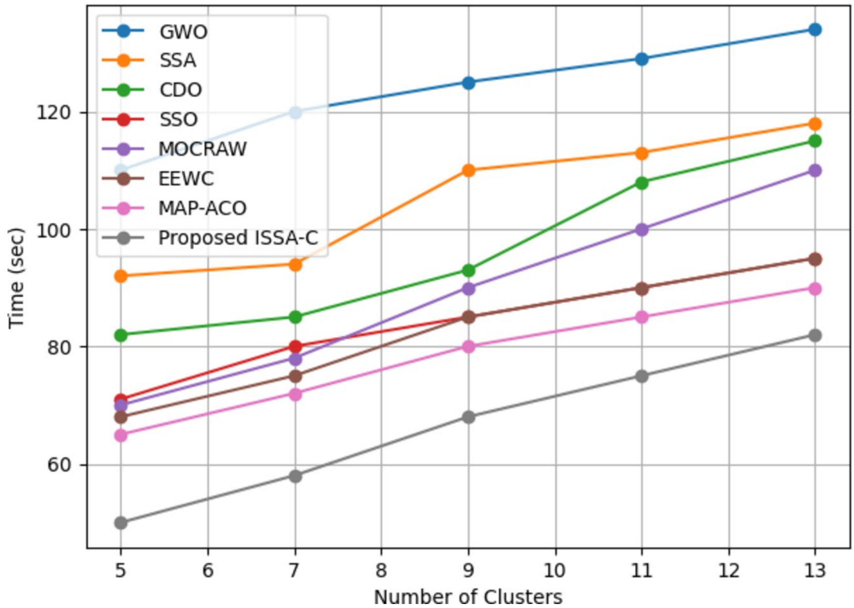

Fig. 9 Numbers of cluster versus Cluster formation time

son to other methodologies, the planned technique is expressively increased. The number of SN upsurges will increase energy consumption. The existing GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO procedures use 320, 300, 280, 260, 240, 230, and 220 MJ of energy.

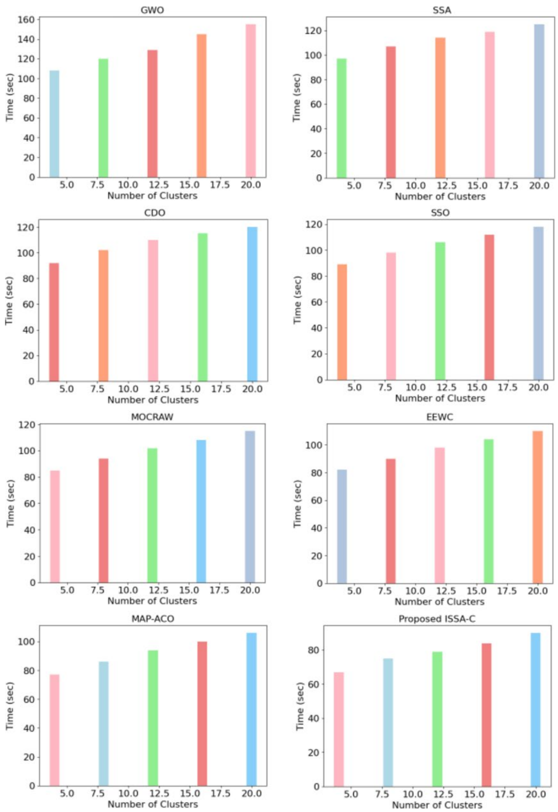

Fig. 10 Time taken for Cluster Head Selection in WSN

5.4 End-to-end delay

The duration of a packet's network journey from its source to its destination is referred to as the "end-to-end delay" (E2ED). This term, which is frequently used in IP network screening, only measures the journey from source to destination in one direction, in contrast to RTT. Figure 5 displays the E2ED research for the suggested and existing techniques. The E2ED of the suggested technique was 10 ms slower than that of other existing systems. The E2ED will increase as the quantity of SNs growths. The relative E2EDs of the current techniques GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO are 11.5, 12, 13, 11.55, 12.5, 12.8, and 13 ms.

5.5 Bit error rate (BER)

Bit errors in digital transmissions are the number of bits that have been altered as a consequence of noise, turbulence, distortion, or bit synchronization problems that have been received as part of a data flow via a communication channel. The rate of bit mistakes about time is known as the bit error rate. The BER evaluation for both existing and proposed approaches is shown in Fig. 6.

In comparison to other existing systems, the suggested approach achieved a lower bit error rate. The bit error rate will climb as nodes become more numerous. The current techniques, GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO, have bit error rates of 30, 28, 22, 18, 14, 16, and 15 correspondingly.

5.6 Buffer occupancy

Figure 7 shows the total buffer occupancy of the suggested plan in contrast to other current plans. The developed system utilised a smaller amount of buffer occupancy (14) in 1000 SNs than other current methods. The graph above demonstrates how, in comparison to other methodologies, the planned technique is expressively increased. The buffer occupancy will climb as the no. of SNs rises. The current GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO protocols use 28, 20, 19, 18, 22, 18, and 20 kilowatt hours, correspondingly.

5.7 Lifetime of a network

The duration of time a system may run and complete the assigned job is known as its lifetime (s). Figure 8 compares the newly created methodology's efficacy with the existing approach over a network. The aforementioned graph displays that the suggested protocol beats previous techniques in terms of system lifespan (5400 cycles).

The system's lifespan shortens as the number of SNs rises. The lifespan of a system is 5000, 4900, 4800, 4700, 4600, 4500, and 4400 rounds for the current approaches GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO, respectively.

5.8 Analysis of time

It displays the total time used in selecting the CH and creating the cluster. The performance of the cluster-building technique over time is shown in Fig. 9. The cluster construction approach that was suggested in this article ran more quickly than in other ways. As there are more clusters, the time will grow. In five clusters, the suggested solution outperformed other current approaches with a shorter execution time (82s).

The performance of the CH selection approach over time is displayed in Fig. 10. The proposed strategy in this paper was quicker to use than the CH selection procedures already in use. If there are more CHs, the time will be extended. The suggested strategy, as shown in Fig. 10, obtained a quick execution time (67s) in five CHs when compared to other current strategies.

In a highly mobile context, the suggested method exhibits enhanced PDR and lowers end-to-end latency. No matter how many sensor hubs are present in the system, the suggested approach may be used right away to speed up execution. In WSNs, temporary connections can lead to packet loss and re-transmissions. In this case, the sensor hub may consume more energy. It can also lower PDR and increase throughput. The suggested method can provide a dependable connection while preserving the energy of the tuned system. Considering this, it seems that the suggested scenario is ideally suited to be ready for extraordinary, flexible situations that match the quality. Applications for real-time data collecting employ the suggested hybrid algorithm.

6 Discussion

This study demonstrates that the I-SSA is highly effective in optimizing cluster head selection for WSNs. The modifications made to the traditional SSA—such as Adaptive Population Initialization, Dynamic Step Size Control, and the integration of a Local Search Algorithm—played a vital role in enhancing the algorithm's convergence rate and solution quality. The comparative analysis of the I-SSA and the existing algorithms such as GWO, SSA, CDO, SSO, MOCRAW, EEWC, and MAP-ACO have proved that the I-SSA is far superior in terms of the proposed performance parameters. Hence, the proposed method increases network lifetime, decreases energy consumption, enhances PDR, and increases throughput, it suggests that the technique has the potential to improve WSNs' duration and efficiency.

The need for energy efficiency in WSNs is the driving force for this investigation. One of the most promising technologies that may be implemented to open up new possibilities for many businesses is WSNs. However, since the sensor nodes that make up WSNs are often battery-powered, power conservation is typically a top priority. Because WSN batteries are not readily replaceable or replenished like those in traditional power sources, optimal energy consumption is critical to extending the lifespan of the network. In order to overcome this obstacle and increase the lifespan of WSNs, the goal of this research is to create a successful CH selection process. Cluster heads are critical components of WSNs because they gather data from SNs and deliver it to base stations.

The practical use of this study is highly applicable to industries that utilize WSNs for monitoring and data acquisition in real-time, including monitoring the environment, agriculture, healthcare, and smart manufacturing. Through better energy utilization and increasing the time between network reparation, the I-SSA may reduce the expenses connected with the replacement and maintenance of the sensor nodes. This is particularly crucial in hard-to-reach places or where physical intervention would be costly and time-consuming. The enhanced PDR and throughput also guarantee the delivery of data which is very essential in decision-making, especially in areas that require accurate and timely information.

However, the study has the following limitations; The simulations were carried out in a controlled environment and this implies that the results may not be very close to the real-world WSN deployments. Key issues like failure of the sensor nodes, delays in communication and interferences of the environment were not considered and these issues may affect the working of the I-SSA in the real world. Further, the study was conducted on a simple WSN environment where all the sensor nodes were of the same type. The behaviour of the I-SSA in different networks where the sensors are different in terms of energy levels and requirements for communication has not been ascertained. Future work should investigate these limitations by conducting experiments with the I-SSA in broader and changing scenarios and by including realistic issues to confirm the efficiency and versatility of the algorithm.

7 Conclusion

In this paper, we assessed the efficiency of the I-SSA in optimizing the clustering and routing for WSNs. The I-SSA-based protocol proposed in the study showed significant enhancements over the existing techniques. The PDR achieved by the proposed I-SSA was 88% and proved to be better than other methods like GWO, SSA, and MAP-ACO which gave PDR of 85%, and 85%. 5%, and 87%, respectively. The throughput results also brought out the idea of the proposed method which when compared to other methods showed a very high improvement. The I-SSA protocol decreased the energy consumption to 210 mJ in 1000 sensor nodes, which is less than the current method's energy consumption of 220–320 MJ. The E2ED for the proposed approach was 10 ms which was slightly better than the 11. Existing methods cost more time, which is ranging from 5 to 13 ms. The BER was also enhanced; the I-SSA offered a better rate than the other techniques like GWO which had a BER of 30 and SSA with a BER of 28. The network lifetime was thus increased to 5400 cycles which was higher than the 4400–5000 cycles of other methods. Thus, the study supports the effectiveness of the I-SSA in improving the WSN performance in terms of various parameters.

Future research can expand the protocol to cover more complicated cases like mobile sensor nodes or different node densities, to evaluate the possibilities of the protocol's usage in different conditions. Exploring energy harvesting technologies may bring the energy consumption level down even lower and increase the network's lifespan. Other possibilities for enhancing the network's reliability could also include real-time adaptability and resilience in the case of node failure or changes in the environment. These advancements could significantly enhance the practical applicability of the I-SSA protocol, contributing to more efficient and adaptable WSN solutions.

Acknowledgements This work was supported by the Researchers Support Project number (RSPD2024R537), King Saud University, Riyadh, Saudi Arabia.

Author contributions I wrote the main manuscript text, prepared figures, and all parts in manuscript.

Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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