



International Journal of Mobile Network Design and Innovation

ISSN online: 1744-2850 - ISSN print: 1744-2869

<https://www.inderscience.com/ijmndi>

Fuzzy dove swarm optimisation based mobile sink clustering routing protocol for wireless sensor network

K. Jayachandran, S. Govindaraju

DOI: [10.1504/IJMNDI.2025.10069678](https://doi.org/10.1504/IJMNDI.2025.10069678)

Article History:

Received:	21 September 2024
Last revised:	28 December 2024
Accepted:	12 January 2025
Published online:	16 June 2025

Fuzzy dove swarm optimisation based mobile sink clustering routing protocol for wireless sensor network

K. Jayachandran* and S. Govindaraju

PG & Research Department of Computer Science,
Sri Ramakrishna College of Arts and Science,
Coimbatore, 641006, Tamil Nadu, India
Email: k.jayachandran1988@gmail.com
Email: kavigovindaraju@gmail.com

*Corresponding author

Abstract: Thousands of resource-constrained sensors work together in a wireless sensor network (WSN) to monitor their environment, gather data, and send it to distant servers for additional processing. Clustering is the most popular topology management technique in WSN, which groups nodes for administration and distributes task execution. The maintenance of energy efficiency in WSN is crucial. This paper introduces a new fuzzy dove swarm optimisation-mobile sink clustering routing (FDSO-MCR) method for the WSN model. The Cluster Head (CH) selection and mobile sink (MS) path identification techniques used by the FDSO algorithm are modelled after the foraging habits of doves in heterogeneous WSN. The nodes are clustered depending on the chosen CH from the FDSO method. It is proposed that several fitness criteria be investigated to ascertain the mobile path of the MS to BS. The MS sends all data to the Base Station using the best path. The suggested method is to collect data multi-hop with MS routing. The suggested algorithm is simulated using MATLABR2021a to compare to other methods. Simulations have used network lifetime, energy usage, BS packet receipts, packet delivery ratio (PDR), and end-to-end (E2E) Delay between routing techniques.

Keywords: WSN; wireless sensor network; FDSO; fuzzy dove swarm optimisation; mobile sink clustering routing (MCR) protocol; clustering; routing protocols; mobile path selection; swarm intelligence (SI).

Reference to this paper should be made as follows: Jayachandran, K. and Govindaraju, S. (2025) 'Fuzzy dove swarm optimisation based mobile sink clustering routing protocol for wireless sensor network', *Int. J. Mobile Network Design and Innovation*, Vol. 11, No. 3, pp.117–133.

Biographical notes: K. Jayachandran is a Part-Time Research Scholar at Sri Ramakrishna College of Arts and Science, Coimbatore. He graduated from Kovai Kalaimagal College, Coimbatore, with a Master's in MSc IT (2010) and MPhil (2012). He is an Assistant Professor with 12 years of teaching experience at Bishop Ambrose College, Coimbatore. His area of research is networking, and he has published in conferences related to wireless sensor networks and UGC CARE journals.

S. Govindaraju is currently working as an Associate Professor PG and Research Department of Computer Science at Sri Ramakrishna College of Arts and Science (Formerly SNR Sons College), Bharathiar University, Coimbatore. He has published more than 29 research papers in reputed international journals, including Thomson Reuters (SCOPUS) and conferences, and it's also available online. His main research work focuses on image retrieval using medical images. He has 17 years of teaching experience and 12 years of research experience.

1 Introduction

These networks have drawn a lot of interest because they are used frequently and because wireless networks make communication simple. The ability to be used in any environment without requiring physical infrastructure, physical communications, environmental monitoring, or engineering is a distinctive characteristic of these networks

that has prompted an increase in wireless networks across various industries (Abinavkrishnaa et al., 2023). Wireless sensor networks (WSNs) have recently become one of the most crucial methodologies worldwide. A self-organising wireless network system known as a WSN is identified by many energy-constrained micro sensors and at least one sink Base Station (BS) (Nandi et al., 2019; Zhang and Zhang, 2018). A WSN comprises big, low-power sensor

nodes with intelligence and a high-power sink, each in charge of creating their connections while following specific transmission rules.

Military and civil engineering (such as environmental monitoring, healthcare, and disaster predictions) are only a few potential uses for sensor-based systems (Anitha et al., 2023). As a result, there are now more problems with sending and receiving information due to the growing use of WSN, with routing these networks posing the biggest problem (Aragani, 2024). Despite having many applications, WSN encounters numerous standard problems, such as limited energy sources, processing speed, memory, and transmission bandwidth, which causes the sensor network to function poorly and shorten its lifetime (Nayak et al., 2021). It can be not easy to create distinct algorithms for various purposes (Banala, 2024). The designer of a WSN should focus in particular on several concerns, including energy limitation (Dhurgadevi and Meenakshi Devi, 2018), security (Musale and Chaudhari, 2017), data aggregation, clustering, routing, localisation, fault detection, task scheduling, event tracking, etc. (Boye, 2024). These difficulties are difficult to handle because they clash with one another (Chundru, 2024).

Most energy is consumed when a data packet is routed from the source node to the destination through a single hop or multiple hops, making routing one of the most crucial activities (Dhinakaran et al., 2023). The network creation of clustering and routing protocols is one of the most important strategies for node energy conservation (Gandhi et al., 2024). Therefore, one of the fundamental strategies to save the node battery is to plan an energy-aware routing system (Harendharan and Boussi Rahmouni, 2023). In addition, WSNs are divided into homogeneous and heterogeneous networks based on their characteristics (Jasper et al., 2024). These strategies include clustering, which is regarded as an effective and scalable energy method for WSNs (Lee et al., 2017). Sensors are grouped into clusters, and CH is used for clustering in WSN. Periodically or after an incident, the sensors in each cluster send CH the pertinent data (Jeba et al., 2024). Then, either directly or via a multi-hop method, CH delivers the data to a BS. Using clustering, you can keep the exchange of messages from repeating and keep the communication bandwidth up (Karthik et al., 2024). By reducing communication costs caused by node interactions with CH alone, clustering can stabilise the network architecture at the sensor level (Kumar Nomula, 2023). In a network, clustering can be used to apply improved management techniques (Kuppam et al., 2024). Scalability, an effective data collecting and CH selection mechanism, and a reduction in communication between cluster heads and base stations are all requirements for the solution (Chundru, 2024).

Fuzzy logic will be used in the proposed protocol since it is very good at handling the uncertainties and dynamics of WSNs (Chunduri et al., 2024). Fuzzy logic is not like the traditional binary systems of logic (Licaj and Karras, 2024). It is a subtle approach because it handles multiple input

parameters such as residual energy, distance to the mobile sink, and node density (Minu et al., 2023). This allows it to make optimum and adaptive decisions crucial to efficient clustering and routing (Nanban et al., 2024). Fuzzy logic lets the protocol flexibly make decisions toward finding an equilibrium in network performance metrics on both energy consumption and coverage (Verma et al., 2018) alongside communication efficiency. Besides this, its interpretation capability for fuzzy data aligns with the unproductiveness of WSN as well since the nodes which compose it can vary in their reliability and status (Nanban et al., 2024). Contrary to the conventional mechanisms of decision-making, fuzzy logic significantly leads to adaptability and resistance, which enhances resource usage along with the extension of the life of the network. This application has chosen fuzzy logic over the other alternatives because of its previous success in similar environments with complex multi-parameter requirements (Paramasivan et al., 2024). It does not introduce any computational overhead with strong solutions and is, therefore, quite suitable for resource-constrained networks (Parveen Roja et al., 2024). With fuzzy logic integrated into the clustering and routing process, this protocol thus ensures that network conditions can be dynamically changed, resulting in better overall performance results (Pranav et al., 2024). This innovative integration shows how pliable fuzzy logic is, even while setting a benchmark for handling the intrinsic problems of WSNs in an efficient and scalable way (Musale and Chaudhari, 2017).

By leveraging sink nodes, CH is spared from having to handle an excessive amount of work while also saving time and energy. As a result, the network can grow while maintaining its efficiency (Mostafaei, 2019; Verma et al., 2018). Updates to the MS position to source sensor nodes are necessary for WSN scenarios (Raj et al., 2024). Network packet loss is substantial in these circumstances, making efficient data collecting impossible (Raja et al., 2024). Researchers have concentrated on creating suitable mobile routing schemes that call for MS to update its location in WSN (Mohemed et al., 2017; Khan and Pathan, 2018).

This section of the research includes a concentrated summary of fuzzy dove swarm optimisation-based mobile sink clustering routing, FDSO-MCR, one of the proposed techniques for WSN (Zhang and Zhang, 2018). It also explains the difficulty of energy efficiency, load balancing, and scalability during WSNs and this innovative characteristic of FDSO-MCR (Rajasekaran et al., 2023). An additional discussion above on the reasons for using advanced methods of optimisation in routing as well as clustering (Rajest et al., 2024). However, the introduction can be stretched into more concurrent methodologies and better technological upgrades of WSNs, making it better in-depth and contextual aptness (Verma et al., 2018). Compared to modern approaches like ant colony optimisation (ACO), particle swarm optimisation (PSO), and Genetic Algorithms, it would be more understandable to the reader how this proposed approach develops more into

something new and different from the existing framework (Sajini et al., 2023). The introduction can elaborate more and explain why the FDSO-MCR model is crucial (Sayedelahl and Farouk, 2024). However, it has provided a good base for the research, emphasising that in heterogeneous WSN, there is a dire need for adaptive clustering and routing schemes to increase the network lifetime and improve efficiency (Kooshari et al., 2023). Making an equitable and energy-saving CH selection and sink mobility are the two main objectives of the suggested study (Shalom Soji et al., 2024). It is assumed that the optimisation strategy can solve the CH selection problem. To balance energy efficiency, many approaches apply an optimisation method (Kooshari et al., 2023; Sun et al., 2020). Theoretically and practically, these methods have been successfully used for WSN clustering and routing challenges. Creating a SI algorithm that solves optimisation problems more effectively has always been a goal. Dove swarm optimisation (DSO), which considers foraging competition, aims to achieve both optimisation and the most contented dove (Soji et al., 2024a).

This paper introduces FDSO-MCR for WSN. The proposed approach provides a robust CH selection mechanism for WSN, using fitness parameters for clustering. In the proposed approach, adaptive MS path planning is carried out in WSN for MS trajectory identification while taking several fitness metrics for cluster formation. Performance parameters have been measured for simulation analysis between the proposed system and existing routing methods.

2 Literature review

An energy-aware path construction (EAPC) algorithm was introduced by Wen et al. (2017). It has been used to select the most probable selection of data collection points, which builds a data collection path, and data gathered from the points are greatly overloaded with data. EAPC considers the forwarding load of each sensor node with the path cost from the current data gathering point to the next point to increase the network lifetime. Data communication is efficient but is not supported by this algorithm (Soji et al., 2024b).

A multi-objective particle swarm optimisation (MOPSO) technique was introduced by Kaswan et al. (2018) for an energy-efficient trajectory. The algorithm is provided with a successful multi-objective fitness function and an effective particle encoding scheme. Pareto dominance is introduced in MOPSO to get the local and global optimal guides for each particle. The proposed algorithm results contradict the Tree Cluster Data Gathering Algorithm (TCBDGA) and the energy aware sink relocation (EASR). The results show that the suggested method outperforms both of them in terms of several performance criteria. The statistical tests of analysis of variance (ANOVA) and its least significant difference (LSD) post hoc analysis are also used to validate the results (Srilakshmi et al., 2024).

A literature review is done efficiently to summarise the existing work on WSN optimisation; it provides a critical overview of clustering and routing techniques. It also elaborates on how optimisation techniques have evolved, focusing on the limitations of traditional WSN optimisation approaches due to WSN requirements' dynamicity. However, this is more elongated, and a systematic review could have complemented the discussion quite effectively (Musale and Chaudhari, 2017). In particular, much more emphasis on compatibility metrics and minimum range of adaptability in the prior approaches will be more helpful. Including a chronological or thematic sequence of methodologies with a corresponding discussion regarding their applicability to the different WSN scenarios can make the discussion richer and more contextual. For example, with the increment of development toward adaptive mobile sink techniques brought under-emphasis, the need for FDSO-MCR will be understood, strengthening the argument toward the proposed model (Kooshari et al., 2023). A literature review proves difficult because of scalability challenges and real-time adaptability that demands energy efficiency. Even though this review is highly rich in completeness concerning the analysis put within the field, going into more detailed performance metrics and factors of compatibility will further help make the review more enriching. This would mean that the point connecting the existing challenges and the novelty of the proposed method would be much enhanced (Wen et al., 2017).

Tabibi and Ghaffari (2019) presented a particle swarm optimisation based selection (PSOBS) for CH selection. Using PSO, the proposed method can locate ideal or nearly ideal rendezvous points for effective network resource management. According to the proposed technique, each sensor node's weight value is also determined depending on the data packets from other sensor nodes. Metrics like throughput, energy consumption, the number of rendezvous locations, and hop count have been introduced to obtain results for the proposed technique and the weighted rendezvous planning based selection (WRPBS) algorithm.

He et al. (2019) introduced the energy-efficient trajectory planning (EETP) algorithm based on MOPSO for reducing the trajectory length of the mobile sink and balance the load on rendezvous nodes. EETP is to shorten data delivery delays and increase network longevity. It is used to choose prospective visiting places by the communication overlapping ranges of the sensor nodes to decrease the route length of the mobile sink. Additionally, a successful trajectory encoding technique is developed that may produce a trajectory with an arbitrary number of visiting spots by the mobile sink trajectory parameters (Sundararajan et al., 2023).

Wang et al. (2018) proposed an improved ACO algorithm for WSN with CH distances. The network is segmented into many clusters for this study, each containing one CH. The mobile sink node determines an ideal mobility trajectory to interact with CH under the improved ACO algorithm. Simulation findings demonstrate that the proposed methodology can greatly increase WSN

performance. Vijayalakshmi and Anandan (2019) focused on selecting the ideal path in routing, which increases the network lifetime and energy efficiency of WSN. A poor local optima problem has been encountered when using several meta-heuristic techniques, including PSO. PSO and Tabu Search (TS) algorithms are the foundation of the suggested approach. Results demonstrate the effectiveness of the suggested Tabu PSO by increasing the number of clusters created and the percentage of active nodes, as well as by demonstrating a decrease in average packet loss rate and average E2E delay. The analysis findings and performance indicators are both inadequate.

By examining mobile sink balance from three perspectives, data collection maximisation, mobile route length minimisation, and network reliability optimisation were examined by Vijayashree and Suresh Ghana Dhas (2019). It concentrated on a large-scale and intensive WSN that permits a certain level of data delay. According to simulation results, the proposed algorithm may effectively reduce data transmission, conserve energy, increase the efficiency and reliability of network data collection, and lengthen the lifetime of the network when compared to existing algorithms like Random Walk and ACO. Delay and PDR indicators are not taken into account.

A balanced power-aware clustering and routing protocol (BPA-CRP) has been introduced by Darabkh et al. (2019). The sensor field is divided into equal-sized layers and clusters using a network topology in the batch-based clustering and routing protocol. Thanks to the clustering technique, a cluster can run numerous rounds without the requirement for setup overhead. BPA-CRP gives each sensor one of four different broadcast ranges. BPA-CRP introduces the idea that a batch ends when any of the forwarder energy levels fall below a predetermined level. Simulation results show that the BPA-CRP system performed better when compared to other methods in terms of network lifetime and energy utilisation (Thirunagalingam, 2024).

Saho et al. (2020) developed a particle swarm optimisation with energy-efficient clustering and sink mobility (PSO-ECSM) protocol. To choose a CH, five parameters are residual energy, distance, node degree, average energy, and energy consumption rate (ECR). PSO-ECSM algorithm is used to identify the best value for these variables. PSO-ECSM protocol has been introduced, which sinks mobility to handle the issue of relaying data traffic in a multi-hop network. This research ignores measures of delay and PDR.

Dynamic Mobility and Energy Aware Algorithm (DMEAAL) was proposed by Thomson et al. (2021). Using a cross-layer approach, DMEAAL builds on existing solutions that use a communication threshold between static nodes and a sink node with a predictable mobility pattern. It uses present energy consumption and dynamically regulates the communication threshold size depending on target energy consumption. This algorithm balances energy consumption diagonally on individual nodes without increasing total energy usage. Mobile edge computing

(MEC) apps remove some functionality from static nodes and deploy it inside the mobile sink at the network edge. Metrics are limited, and the analysis findings are inadequate (Usman and Ullah, 2024).

Yalçın and Erdem (2022) proposed a thermal exchange optimisation (TEO) inspired by the Newton cooling rule for mobile clustering routing systems. With separate fitness parameters as objective functions, two distinct methods are provided in the current protocol for CH selection and MS path recognition. CH selection and MS trajectory algorithm have been introduced for each mobile round by the temperature in the TEO algorithm, which minimises loss and reduces the network delay. The performance results of the proposed protocol work better when compared to other techniques.

3 Proposed methodology

This paper introduces a new FDSO-MCR method for the WSN model. CH selection and MS path detection in heterogeneous WSN are two foraging behaviours of doves that inspired the FDSO algorithm. The proposed method uses WSN to execute adaptive MS path planning while considering several fitness parameters for cluster formation. Depending on the chosen CH from the FDSO method, the nodes are clustered, and data is transmitted from source to destination.

This part should be structured and detailed for clarity and accessibility. The discussion should be divided into smaller, easily digestible steps for readers to intuitively know to follow the workflow that begins with problem definition and moves forward through parameter initialisation to cluster formation, routing decisions, and performance evaluation. Although the step-by-step explanation supported by diagrams simplifies understanding, it presents logically what had been in the implementation of the protocol. Such an approach could be presented with illustrative examples of processes like clustering sink mobility patterns to present the gaps. Subheadings and flowcharts help readers with little knowledge of the concepts behind the work to better navigate and relate to the subject. For example, illustrations may be applied to illustrate operations crucial to the theory, such as fuzzy logic in decision-making or Dove Swarm Optimisation (Zanardo, 2024a). This refines the section with modular explanation, thus revealing the adaptability and scalability of the protocol and showing relevance to diverse WSN scenarios. Enhanced clarity also builds confidence in the methodology's rigour, so the research is perceived as systematic and replicable. This will solidify the reader's understanding while aligning with the goals of offering a robust and transparent research process, which is crucial to gaining acceptance in the academic and practical domains (Venkat Narayan et al., 2023).

A comprehensive comparative analysis of the proposed protocol with the existing well-known counterparts such as LEACH and PEGASIS further supports its supremacy and practicality. Although popular for its randomised selection

of cluster heads, LEACH has the problem of premature energy drain due to the non-uniform distribution of energy usage in the nodes. PEGASIS, though reducing energy consumption by making communication in a chain, incurs considerable latency and computational overhead, which is not preferable for dynamic WSNs (Vignesh Raja et al., 2023). The proposed protocol uses fuzzy logic and mobile sinks to adjust clustering and routing dynamically. This eliminates the static clustering limitation and the high communication overhead. Energy efficiency, packet delivery ratio (PDR), and latency are consistent performance metrics favouring the proposed approach (Zanardo, 2024b). Simulations demonstrate a prolonged network lifetime due to balanced energy consumption across nodes and increased packet delivery reliability, even in complex and dynamic scenarios. Mobile sink integration will further reduce the communication distances and latency, thus increasing throughput overall. This detailed comparison not only proves the viability of the protocol but further underlines its ability to address the real-world difficulties that come with it. Superior performance on traditional metrics places the research's protocol squarely in competition with current approaches, highlighting this potential for resource-constrained WSNs to change.

3.1 Objective function

The aim is to use various fitness criteria to enhance network performance while assigning the least expensive nodes as CH. The compatibility variables used to increase network lifetime and decrease energy depletion are called fitness parameters. The following descriptions of the fitness parameters are discussed clearly.

Remaining energy of a sensor node: Sensor node's remaining energy Fi_{res} is one of the fitness metrics. En_{ri} stands for the remaining energy of node i , and En_i stands for the network's overall energy. In this way, the network experiences balanced energy depletion. Equation (1) illustrates how this parameter was calculated.

$$Fi_{res} = \sum_{i=1}^n \frac{En_{ri}}{En_i} \quad (1)$$

The entire number of nodes is n . A node with low Fi_{res} has a higher chance of being selected as a CH.

An average node energy: Equation (2) is used to calculate Fn_{avg} , and it is then normalised to a value between 0 and 1. Here, En_i is the node i remaining energy.

$$Fi_{avg} = \frac{1}{n} \sum_{i=1}^n En_i \quad (2)$$

Distance of a node with MS: Node distance from the MS is measured using fitness parameters (Fi_{dist}). Consequently, it is essential to use this parameter as a starting point to

determine a more accurate objective function. Equation (3) gives the value of Fi_{dist} .

$$Fi_{dist} = \sum_{i=1}^n \frac{dis(n_i \text{ to } MS)}{dis(navg_i \text{ to } MS)} \quad (3)$$

where $dis(n_i \text{ to } MS)$ and $dis(navg_i \text{ to } MS)$ represent the average and Euclidean distance of node i to the MS correspondingly. The node total number (n) is determined by the assumption that they are aware of their positions to the global positioning system (GPS). The likelihood that a node is a CH increases with decreasing distance from the MS node.

Number of neighbours surrounding a node: When choosing a CH, it is important to consider the number of neighbours around a node. The fitness parameter Fi_{neig} represents the number of node neighbours provided in equation (4).

$$Fi_{neig} = \frac{\sum_{i=1, j=1}^{n_{cl}} dis(i, j)}{n_{cl}} \quad (4)$$

where n_{cl} is the number of nodes in the cluster, and $dis(i, j)$ denotes the distance between nodes i and j . In order to choose the optimum CH, this parameter should also be decreased. The objective function and fitness parameters are added together, and the result is obtained as in equation (5).

$$Fi_{obj} = \varphi_1 * Fi_{res} + \varphi_2 * Fi_{avg} + \varphi_3 * Fi_{dist} + \varphi_4 * Fi_{neig} \quad (5)$$

where the fitness parameters are multiplied by the weighting coefficients $\varphi = 0.25, \varphi_2 = 0.25, \varphi_3 = 0.25, \varphi_4 = 0.25$, and their sum is 1. In this case, the value of Fi_{obj} should be as low as possible to enable the best CH selection and enhance network lifetime performance.

3.2 Fuzzy dove swarm optimisation (FDSO)

The fuzzy dove swarm optimisation (FDSO) algorithm mimics the foraging habits of doves is introduced (Su et al., 2022). Fi_{obj} (N) is the optimisation objective function used in the DSO method. In a WSN model, each node pattern, N , is viewed as a node position with crumbs, and the number of crumbs present in this location (N) has the objective function $f(N)$ crumbs.

Step 1: Choose how many doves to send out into the CH solution. Assume that N is the predetermined number of doves. By placing these doves consistently throughout a rectangular area, it is possible to scatter them randomly throughout the area.

Step 2: Decide on the number of epochs $e = 0$ and the satiety level s_d^e for dove $d, d = 1, \dots, N$. There are two

methods for initialising the node position vector $W_d \subset R^M$ of dove d . The easiest method is to initialise W_d at random, centered on the CH solution. The alternative is to initialise a method that uses a lattice. The actions are depicted as follows:

Two effective weight initialisation strategies are given to speed up the training process for creating a topologically ordered node map. Let define the smallest hyper-rectangle for the parameter space as $[lo_1, up_1], \dots, [lo_M, up_M]$. It contains all of the allowed values for all of the parameters. The a -dimension lower and upper bounds in the CH selection space are denoted by the letters lo_a and up_a . These are the specific steps:

Step 2-1. Initialisation of the network four corners cells by equations (7)–(10),

$$we_{1,1} = (lo_1, lo_2, \dots, lo_M)^T \quad (7)$$

$$we_{A,B} = (up_1, up_2, \dots, up_M)^T \quad (8)$$

$$we_{1,B} = \left(lo_1, lo_2, \dots, lo_{\frac{M}{2}}, up_{\frac{M}{2}+1}, \dots, up_M \right)^T \quad (9)$$

$$we_{A,1} = \left(up_1, up_2, \dots, up_{\frac{M}{2}}, lo_{\frac{M}{2}+1}, \dots, lo_M \right)^T \quad (10)$$

Step 2-2. Initialisation of the four edge cells using equations (11)–(14)

$$we_{1,j} = \frac{we_{1,B} - we_{1,1}}{B-1} (j-1) + we_{1,1} * fw_{1,1} \quad (11)$$

for $j = 2, \dots, B-1$

$$we_{A,j} = \frac{we_{A,B} - we_{A,1}}{B-1} (j-1) + we_{A,1} * fw_{A,1} \quad (12)$$

for $j = 2, \dots, B-1$

$$we_{i,1} = \frac{we_{A,1} - we_{1,1}}{A-1} (i-1) + we_{1,1} * fw_{1,1} \quad (13)$$

for $i = 2, \dots, A-1$

$$we_{i,B} = \frac{we_{A,B} - we_{1,B}}{A-1} (i-1) + we_{1,B} * fw_{1,B} \quad (14)$$

for $i = 2, \dots, A-1$

$$fw_A(x) = \begin{cases} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x > c \end{cases} \quad (15)$$

In equation (15), $fw_{1,1}, fw_{A,1}, fw_{1,B}$ & $fw_{1,B}$ have been introduced to fuzzy weight generation. The fuzzy membership function does the greatest task of describing

the node fuzziness. Three parameters, a, b , and c , can be used to create the triangle membership function that fuzzifies the input. In equation (15), a specifies the lower bound, and b and c specify the middle and higher bounds for each node. For each node, $A = \{a, b, c\}$, weight x is produced at random.

Step 2-3. The weight vectors for the four neurons in the network corners are initialised in steps 2–3. Start the remaining neurons from left to right and from top to bottom.

$$we_{i,j} = \frac{we_{A,j} - we_{1,j}}{A-1} (i-1) + we_{1,j} \quad (16)$$

Choose a variety of sizes and assess the result. The winning numbers of all neurons should be counted along with the difference value to evaluate the training results. The learning rate initial value is set at 0.1, and its rate of decline is as follows,

$$\eta(n) = \eta_0 * \left(1 - \frac{t}{T} \right) \quad (17)$$

where η_0 is the initial learning rate, and t is the iteration number.

Step 3: Determine the total number of crumbs in the position of the d th dove using the all-dove fitness function $f(we_j^e), j=1, \dots, N$ epoch.

Step 4: Find the dove d_j^e that is closest to the most crumbs using the highest criterion at epoch e .

$$d_j^e = \arg \max \{ f(we_j^e) \}, \text{ for } j = 1, \dots, N \quad (18)$$

Step 5: Apply equation (19) to update each dove's satiety level.

$$S_j^e = \lambda S_j^{e-1} + e^{(f(we_j^e) - f(we_{d_j^e}^e))}, \text{ for } j = 1, \dots, N \quad (19)$$

Step 6: Utilising the maximal criterion, choose the dove, d_s^e , with the highest level of satiety,

$$d_s^e = \arg \max_{1 \leq j \leq N} \{ S_j^e \}, \text{ for } j = 1, \dots, N \quad (20)$$

The dove d_s^e , identified by equation (20), is the one which exhibits the finest foraging behaviour and it is deserving of imitation by the other doves in the flock.

Step 7: Apply the maximum criterion to each dove position vector,

$$we_j^{e+1} = we_j^e + \eta \beta_j^e (we_{d_s^e}^e - we_j^e) \quad (21)$$

$$\beta_j^e = \left(\frac{S_{d_s^e}^e - S_j^e}{S_{d_s^e}^e} \right) \left(1 - \frac{we_j^e - we_{d_s^e}^e}{\maxDistance} \right) \quad (22)$$

$$\maxDistance : \max_{1 \leq j \leq N} we_j - we_i \quad (23)$$

The parameter (η) represents the learning rate used to update the dove position vector. The updating is explained in full in the next step using equations (21)–(23).

Step 8: Continue to step 3 and add one more epoch ($e = e + 1$) until the termination condition is satisfied. Following is the termination condition,

$$|f_{d_s}^e - T(e)| \leq \varepsilon \text{ or } e \leq \text{the set max epoch} \quad (24)$$

The number of epochs, N , and the number of doves all contribute to the DSO algorithm order of complexity, which is $O(NN_d e)$. Equations (16) and (17) can be changed to equations (25) and (26) if the optimisation is based on the criterion is the best way to locate the minimum (we_j^e).

$$d_j^e = \arg \min \{f(we_j^e)\}, \text{ for } j = 1, \dots, N \quad (25)$$

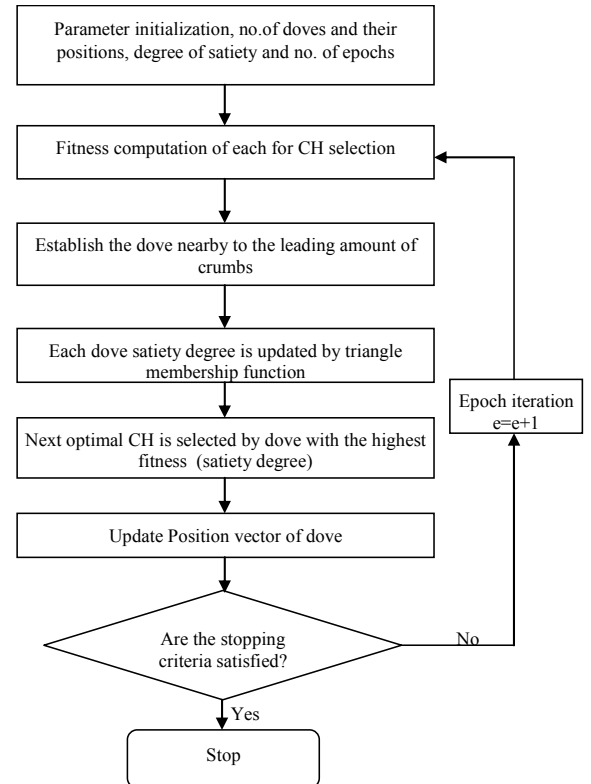
$$S_j^e = \begin{cases} \lambda S_j^{e-1} + e^{(f(we_j) - f(we_{df}))}, & \text{if } f(we_{df}) \neq 0 \\ \lambda S_j^{e-1} + 1, & \text{if } f(we_{df}) = 0, \text{ for } j = 1, \dots, N \end{cases} \quad (26)$$

An individual node strives to emulate the behaviour of the best CH in the flock in response to the best individual (CH)'s success. In order to find more food, doves gravitate toward the dove, who exhibits the highest level of satiety. A dove is more likely to become conservative and hesitate to alter its current foraging strategy when it is more satiated. On the other hand, a dove with a lower level of satisfaction would likely be more motivated to alter its current foraging strategy and be more eager to mimic the actions of the best CH. Figure 1 shows the general flowchart of the proposed system. In detail, the description will involve the FDSO-MCR approach, which focuses on WSN and how it is applied in adaptive mobile sink path planning. It uses such fitness parameters as residual energy, node density, and distance to ensure efficient cluster formation. These parameters underscore the adaptability and effectiveness of the proposed method across various exploitation scenarios. However, summarising the above section without losing technical clarity would help the readers. The above discussion can be supplemented with a step-by-step algorithmic process as a flowchart or diagram for clarity in understanding. In addition, it will be more convincing if the method has a brief comparative analysis with the present optimisation methods. This adaptive mobile sink path planning mechanism is an important contribution since it deals well with the issues of energy dissipation and network imbalance. The focus, however, should be on specific challenges that may have arisen during its implementation to make the methodology rich. A summarised yet precise expression of the detailed explanation would enrich its presentation and engrossment.

This protocol offers computationally efficient complexity and is highly scalable for large WSNs. Moreover, the integration of fuzzy logic ensures the correctness of clustering and routing decisions without

many computational overheads involving multiple parameters inputted and without tedious calculations involved. DSO even enhances this by choosing lightweight iterative optimisation processes that yield speedy convergence to better solutions. This makes the complexity dominated by the number of sensor nodes and the number of formed clusters. Still, by dynamically ensuring a mechanism, there would be an equal spread of energy over the entire network, thus minimising wastage with network size, as it adapts and prohibits its behaviour towards excess usage of resources with reallocations in energy and communication tasks. This scalability is much needed in real-world settings where WSNs are large and sparse. Moreover, the computational cost of implementing fuzzy logic and DSO is still within acceptable ranges for resource-constrained nodes. The low time and energy complexity combined with a high-performance guarantee makes the protocol feasible in practical applications. This balance between efficiency and scalability offers robust appropriateness toward dynamic and large-scale environments for WSNs and represents a robust approach toward growing network demands.

Figure 1 Flow chart of FDSO algorithm



3.3 MS path detection method

MS path identification has been established to update the exact paths from MS to CH using various fitness factors with algorithmic crumbs changes. It has been used to identify the least expensive approaches to enhance network performance.

The remaining CH: MS path energy is determined by this parameter to primary CH. En_{ch-ri} and N_{cl} is denoted as the residual energy and total sum of the CH node i are connected to fitness parameters Fi_{res}^m . Equation (27) illustrates this parameter,

$$Fi_{res}^m = \sum_{i=1}^{N_d} En_{ch-ri} \quad (27)$$

Distance between a CH and an MS: The distance between a CH and an MS (Fi_{dist}^m) is another fitness criterion. Data from CH is nearer the MS and can be delivered to MS more quickly. Equation (28), which contains Fi_{dist}^m ,

$$Fi_{dist}^m = \sum_{i=1}^{N_d} \frac{dis(CH_i \text{ to } MS)}{dis(avgCH_i \text{ to } MS)} \quad (28)$$

where $dis(CH_i \text{ to } MS)$ and $dis(avgCH_i \text{ to } MS)$ denote the distance and average distance, respectively, between a CH node and the MS. Lower values of Fi_{dist}^m propose that the current CH_i could potentially serve as the MS's next address.

No. of the nodes in a cluster: The energy consumption of the cluster increases with cluster density. Therefore, this value should likewise be minimised to limit the energy used throughout the MS trajectory. In equation (29), Fi_{cm}^m is specified. Here, $N_{cm(i)}$ denotes the number of the CH node cluster member nodes.

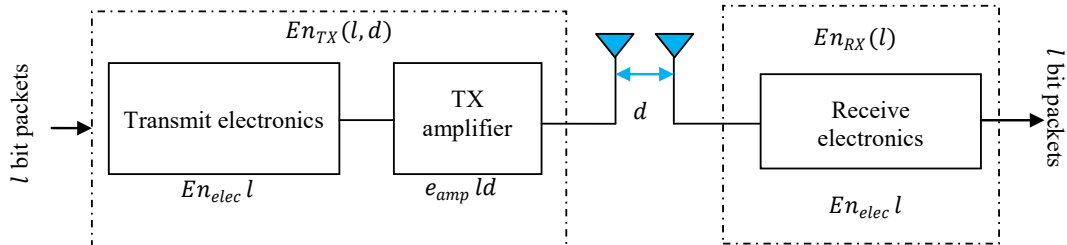
$$Fi_{cm}^m = \sum_{i=1}^{N_d} N_{cm(i)} \quad (29)$$

The objective function and the fitness parameters Fi_{obj}^m are then combined according to equation (30).

$$Fi_{obj}^m = \varphi_1 * Fi_{res}^m + \varphi_2 * Fi_{dist}^m + \varphi_3 * Fi_{cm}^m \quad (30)$$

where the fitness parameters are multiplied by the weighting coefficients $\varphi_1 = 0.33, \varphi_2 = 0.33$ and $\varphi_3 = 0.33$, and their sum is $(\varphi_1 + \varphi_2 + \varphi_3 = 1)$. In this case, the value of Fi_{obj}^m must be as low as possible to find the optimum MS path and enhance network performance.

Figure 3 Energy consumption model (see online version for colours)



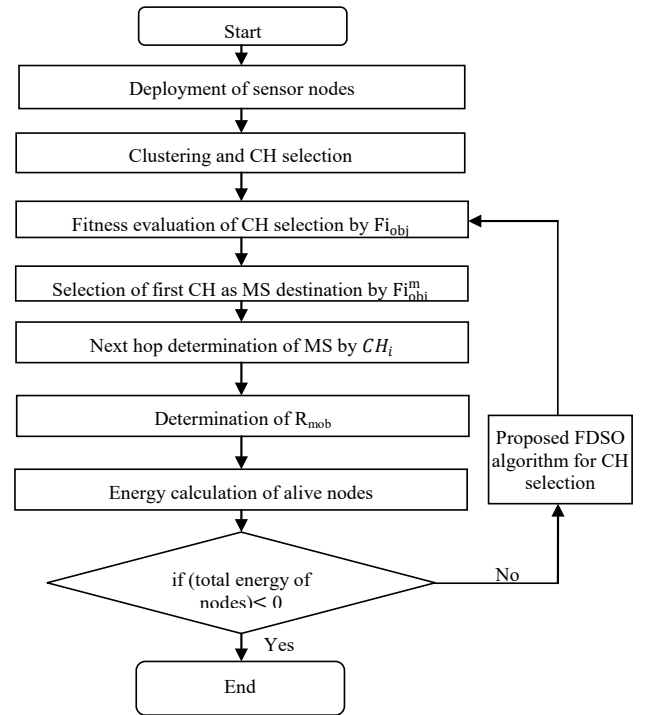
The network energy depletion model is shown in Figure 3. In Figure 3, d is denoted as the distance between the Transmit amplifier and the receive electronics, l is the

Following the distribution of nodes across the network, as depicted in Figure 2, CH is chosen by the CH selection objective function. The primary CH is then designated as the MS pathway begins. By providing the appropriate CH and MS routing objective function, the MS trajectory R_{mob} is achieved. Each round involves computing the number of living nodes in the network. Dead nodes that waste energy are not sent echo packets, and the network cuts off their connectivity. These procedures continue until all of the energy for each round, as indicated in the energy model, is used up.

3.4 Energy consumption model

The energy model in recent work was applied for energy efficiency (Yalçın and Erdem, 2020, 2022). Equation (31) is used in energy depletion models to compute the energy required for sending and receiving data $En_{TX} = En_{RX}$.

Figure 2 MS path detection scheme



amount of data, En_{da} and En_{elec} is denoted as data acquisition energy and electronic power of the transmitter/receiver, respectively, e_{fs} and e_{amp} is denoted as

the diverse category of radio amplifiers designed for unfilled and multi-paths. The energy depletion model is displayed in $En_{\frac{TX}{RX}}(l, d)$ for l bits.

$$En_{\frac{TX}{RX}}(l, d) = \begin{cases} l(En_{elec} + e_{fs}d^2), & d < d_0 \\ l(En_{elec} + En_{da} + e_{amp}d^4), & d \geq d_0 \end{cases} \quad (31)$$

The reference distance d_0 is calculated in equation (32).

$$d_0 = \sqrt{\frac{e_{fs}}{e_{amp}}} \quad (32)$$

As a result, equation (33) for node i in round r calculates the overall energy consumption En_i^r .

$$En_i^r = En_{Tx}(l, d) * nd_i + En_{RX}(l, d) * (nd_i - S_i) \quad (33)$$

where nd_i and nd_j stand for the corresponding transmission loads of nodes i and j . The node next to node i is node j . Node i is supposed to have generated S_i packets for each round. Equation (34) computes the value of nd_i . In this case, the cluster member number is f_i when node i is a CH.

$$nd_i = \begin{cases} \sum_{j \in f_i} nd_j + S_i, & \text{if } f_i \neq \emptyset \\ S_i, & \text{else} \end{cases} \quad (34)$$

Received signal strength indicator (RSSI) parameter calculates the distance between each node and its surrounding nodes. N_{nrm} , N_{adv} and, N_{sup} is denoted as the amount of normal, advanced, and supernodes. Equation (35) has been used to calculate the total number of nodes n .

$$n = N_{nrm} + N_{adv} + N_{sup} \quad (35)$$

En_{nrm} , En_{adv} and En_{sup} is represented as the energy used for normal, advanced, and super nodes correspondingly. It has been described by equations (36)–(38) (Yalçın and Erdem, 2020). Here, $\omega=1$ and $\theta=2$ adjust the energy usage of advanced and super nodes, respectively.

$$En_{nrm} = En_0 \times N_{nrm} \quad (36)$$

$$En_{adv} = \omega \times En_0 \times N_{adv} \times (1 + \sigma) \quad (37)$$

$$En_{sup} = \theta \times En_0 \times N_{sup} \times (1 + \mu) \quad (38)$$

where the energy coefficients are $\sigma=0.002$ and $\mu=0.003$, respectively, these coefficients are fractionally added together to equal one. Equation (39), which expresses the network total energy as En_i . Until this energy is depleted, the network will be functional.

$$En_i = En_{nrm} + En_{adv} + En_{sup} \quad (39)$$

The total energy used for energy transmission is described in equation (39).

4 Results and discussion

A computer with a Windows 10 operating system, an Intel core i7 CPU running at 3.9 GHz, 8 GB of RAM, and the MatlabR2021a application were used to perform the algorithms. In Table 1, the simulation parameters are shown. The network is distributed by 100–500 no. of sensor nodes with three levels of heterogeneous nodes (N_{nrm} , N_{adv} , N_{sup}).

Table 1 Simulation parameters

Parameters	Values
No. of sensor nodes	100–500
Network area	100 × 100 m ² , 200 × 200 m ²
Total number of N_{nrm} nodes	$n*0.4$
Total number of N_{adv} nodes	$n*0.3$
Total number of N_{sup} nodes	$n*0.3$
The initial energy of the sensor nodes (En_0)	0.5 J
Packet size	2000 bits
Communication radius	60 m
Coverage radius	30 m
Deployment of the sensor nodes	Uniformly distributed manner
Base station (BS) location	(0,0)
Speed of the MS	10 m/s
amplifier energy reduction by short distance (e_{fs})	10 pJ/bit/m ²
amplifier energy reduction by longer distance (e_{amp})	0.0013 pJ/bit/m ⁴
Electronic circuit energy (E_{elec})	50 nJ/bit
data aggregation energy (E_{da})	5 nJ/bit/signal

4.1 Simulation results metrics

The following performance indicators can be found in simulations: network lifetime, energy consumption, number of packets received by BS, PDR, E2E delay, and network lifetime. Results from a high number of runs of various large numbers of simulations must be obtained to validate the protocol's effectiveness over a wide range of scenarios. It exposes the adaptability and robustness of the protocol to various network sizes, distributions of nodes, and different movements of sinks. Sparse networks reflect the efficiency of the protocol in managing communication over large distances, while dense networks prove their capabilities in optimising clusterisation and redundant data transmissions. A varied range of sink mobility patterns indicated the adaptive characteristics of the protocol in routing and clustering policies, thereby minimising the overall energy consumption and the resultant data reliability. Further simulation under several load conditions in traffic and

different terrains proved its reliability. Its energy efficiency, PDR, and latency have always provided a higher priority to the proposed protocol, which, in return, is the depository of good performance compared with the present schemes, which could be LEACH or PEGASIS. This also shows the protocol's scalability, which can be said to work at bigger and more complex configurations of the networks. Such comprehensive simulations make it possible for the current study to confirm that the protocol is effective in real issues in a WSN, making its practicality and application over a wide range of cases more feasible.

Packet delivery ratio (PDR): PDR is the ratio of total packets delivered to total packets transmitted via the network from the source node to the target node. It can be expressed formally by equation (40):

$$\text{Packet Delivery Ratio (PDR)} = \frac{\sum \text{Total Packets Received by all destination node}}{\sum \text{Total Packets Send by all source node}} \quad (40)$$

Energy consumption: The energy value required to send or receive a message over a distance of d with a length of one unit.

End-to-end delay (E2E): The time a packet is generated at the sensor and the time the sink receives it is known as an E2E delay. It is described by equation (41):

$$\text{End to End Delay} = \sum_{i=1}^k (\text{OneHop}_{\text{Delay}}(i) + C) \quad (41)$$

$$\begin{aligned} \text{OneHop}_{\text{Delay}} = & \text{Processing}_{\text{Delay}} + \text{Queuing}_{\text{Delay}} \\ & + \text{Channel}_{\text{Access Delay}} + \text{Transmission}_{\text{Delay}} \\ & + \text{Propagation}_{\text{Delay}} + \text{Reception}_{\text{Delay}} \end{aligned} \quad (42)$$

Network lifetime (NL): Network lifetime is measured as the amount of time until the initial sensor energy runs out; it is a crucial determining factor in WSN. In a conventional WSN, each sensor node is constructed to use multi-hop communication to relay the data it has gathered to the sink.

More diversified and realistic conditions within a real WSN would make it more practically relevant if deployed or emulated. In the real-world testing of protocols, different node densities, complexities in terrains, and mobility patterns are considered. Such scenarios can be devised to closely resemble real applications for WSNs, like environmental monitoring or disaster management, under which dynamic conditions challenge protocol efficiency. This would be very useful if direct implementation is impossible. More realistic parameters, as well as larger size network simulations, can contribute to that. More reality can be found in heterogeneous nodes, having models of energy consumption and data traffic, which may be varied accordingly. More reviewing and analysing of the protocol

according to more relations with it and real issues about it would be given for. This will also lead to further optimisation based on its performance under assumptions and more testing of which the protocol was built. Such analysis will determine the feasibility of this protocol by considering practical constraints rather than theoretical scenarios. The outcome of such tests will increase a person's confidence in the potential scalability and real-world applicability of the developed protocol towards more extensive scope applications of WSNs.

4.2 Results analysis

Simulation results are analysed using the following metrics,

- Analysis of the network lifetime:* The number of rounds in which every one of the network nodes' energy is consumed is known as network lifetime. Simulation analysis: 100–500 nodes are randomly distributed around the network area for network density analysis.

Utilising WSN1 and WSN2, the routing algorithms were assessed by network lifetime. Figure 4(a) shows that the proposed FDSO-MCR system in a 500 node achieves a higher network lifetime at 61,486 rounds, compared to 50,894, 52,984, and 56,485 rounds for the ACO, PSO-ECSM, and TEO-MCRP respectively. Figure 4(b) shows that the network lifetime for all methods reduces as the network area grows. However, the greatest network lifetime of 58,485 rounds was attained in 500 nodes by the proposed FDSO-MCR system. By providing a quicker and more stable solution using the FDSO, the proposed system can identify the optimal CH and MS pathways. Table 2 lists the specifics of the network's lifetime performance results.

Figure 4 Network lifetime analysis vs. no. of nodes: (a) simulation model 1 (WSN1) and (n) simulation model 2 (WSN2) (see online version for colours)

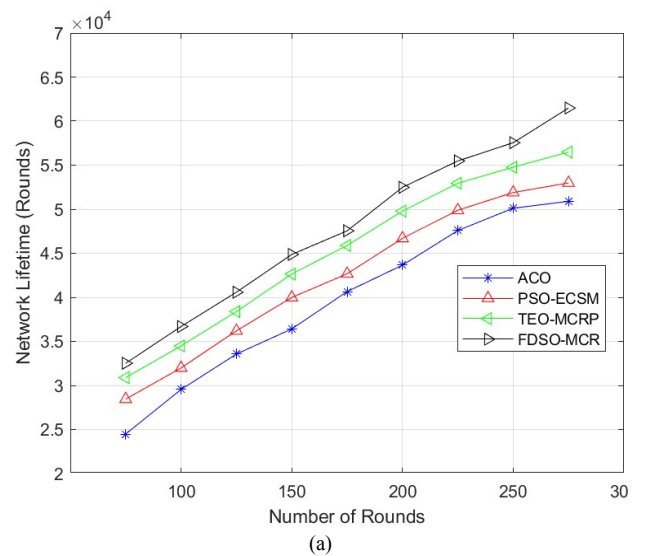
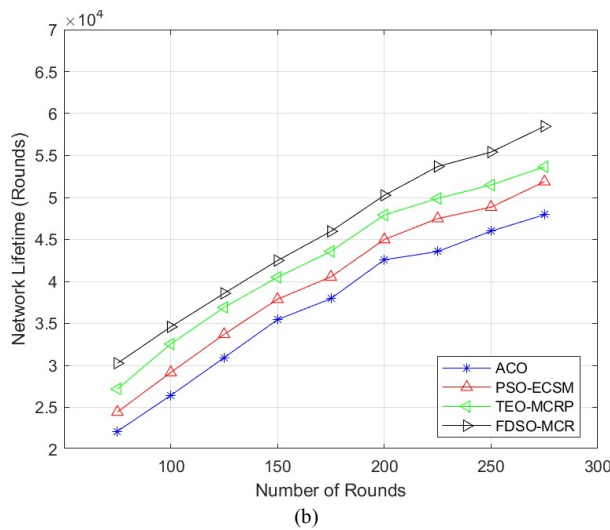


Figure 4 Network lifetime analysis vs. no. of nodes: (a) simulation model 1 (WSN1) and (n) simulation model 2 (WSN2) (see online version for colours) (continued)



b *Energy consumption in the network:* The network's energy starts to decline as soon as data transmission occurs. Consequently, it is crucial to compare the energy used in the network by no. of rounds.

The network total energy consumption is 115.68 J, and a proposed mechanism has produced 119.23 J for WSN1&WSN2, as depicted in Figure 5(a) and (b). Figure 5(b) shows that since WSN2 has an increased network area, energy is consumed more quickly. According to these findings, the FDSO-MCR system uses less energy (119.19 J), while other methods like ACO, PSO-ECSM, and TEO-MCRP require more energy of 156.49 J, 147.55 J, and 132.81 J, respectively (See Table 3).

Figure 5 Energy consumption comparison vs. no. of rounds: (a) simulation model 1 (WSN1) and (b) simulation model 2 (WSN2) (see online version for colours)

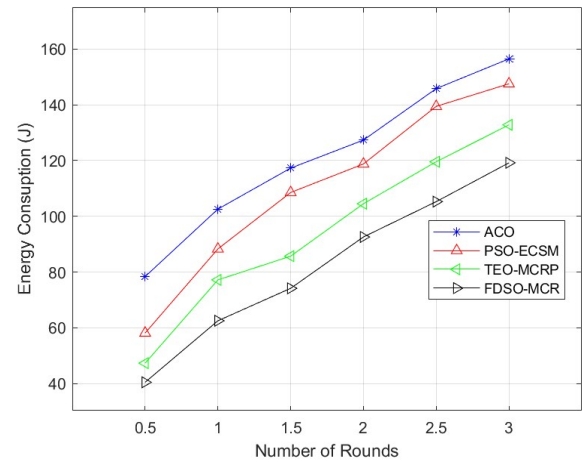
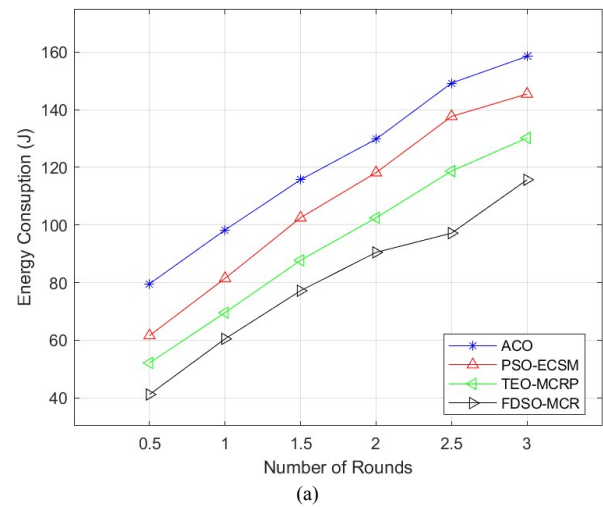


Table 2 Network lifetime comparison vs routing methods

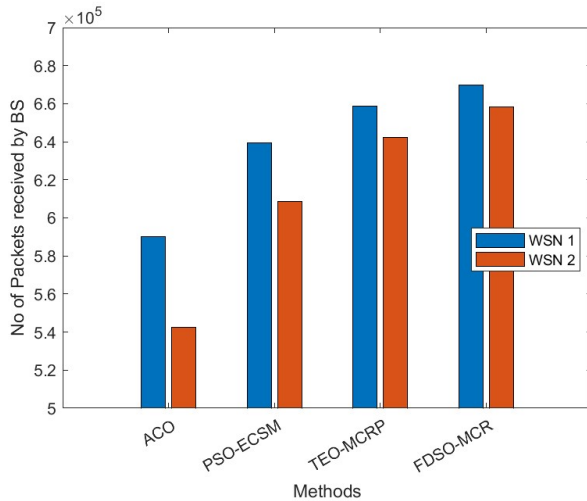
No. of nodes	Network lifetime(Rounds)-Routing methods							
	WSN1				WSN2			
	ACO	PSO-ECSM	TEO-MCRP	FDSO-MCR	ACO	PSO-ECSM	TEO-MCRP	FDSO-MCR
100	24,482	28,445	30,888	32,515	22,145	24,441	27,185	30,251
150	29,541	31,984	34,482	36,684	26,419	29,158	32,545	34,586
200	33,558	36,198	38,391	40,581	30,914	33,697	36,912	38,581
250	36,415	39,985	42,642	44,865	35,447	37,881	40,491	42,488
300	40,651	42,671	45,887	47,547	37,951	40,544	43,581	45,964
350	43,652	46,692	49,785	52,481	42,581	44,985	47,918	50,255
400	47,584	49,887	52,944	55,478	43,558	47,491	49,885	53,692
450	50,114	51,894	54,771	57,547	45,992	48,849	51,489	55,410
500	50,894	52,984	56,485	61,486	47,944	51,881	53,656	58,485

Table 3 Energy consumption analysis vs. routing methods

No. of Rounds * 10 ⁴	Energy consumption (J)-Routing methods							
	WSN1				WSN2			
	ACO	PSO-ECSM	TEO-MCRP	FDSO-MCR	ACO	PSO-ECSM	TEO-MCRP	FDSO-MCR
0.5	79.56	61.58	52.11	41.14	78.36	58.11	47.29	40.44
1.0	98.25	81.44	69.54	60.45	102.58	88.29	77.17	62.51
1.5	115.69	102.49	87.72	77.15	117.29	108.54	85.69	74.15
2.0	129.77	118.14	102.48	90.47	127.34	118.77	104.51	92.58
2.5	149.25	137.67	118.69	97.15	145.81	139.44	119.57	105.25
3.0	158.53	145.45	130.19	115.68	156.49	147.55	132.81	119.23

- c *Analysis of the number of packets received by BS:* When assessing the efficiency of the network, the amount of packets received by the BS must be considered in this section. Utilising WSN1 and WSN2, the routing algorithms were assessed among networks.

In the WSN1 scenario, the proposed FDSO-MCR technique sent 669,802 packets to the BS as opposed to the ACO, PSO-ECSM, and TEO-MCRP approaches, which delivered 589,941, 639,480, and 658,915 packets respectively are illustrated in Figure 6. Although 658,474 packets were supplied to the BS in the WSN2 scenario using the proposed method, 542,548, 608,481, and 642,465 packets were received by the BS using the ACO, PSO-ECSM, and TEO-MCRP methods. Table 4 demonstrates that the proposed approach produces the best results for WSN1 compared to other methods.

Figure 6 Number of packets received by BS vs. WSN1 and WSN2 (see online version for colours)

- d *Analysis of the packet delivery ratio (PDR):* Network performance can be assessed using a PDR statistic. This number shows the proportion of packets accurately delivered to BS with the network. Nodes (100-500) are randomly distributed in the network area according to the number of rounds.

Two scenarios (WSN1 and WSN2) were used to assess different routing strategies. Figure 7(a) demonstrates that

the PDR for the proposed technique is 98.62%; ACO, PSO-ECSM, and TEO-MCRP have produced others like 96.19%, 97.15%, and 97.91% in 100 nodes. Figure 7(b) shows that when the network area grows, the proposed technique yields the highest PDR (92.88%), while other methods such as ACO, PSO-ECSM, and TEO-MCRP yield the lowest PDR of 89.45%, 90.25%, and 91.24% for 500 nodes (See Table 5). The findings demonstrate that the proposed approach achieves the maximum PDR due to the best CH selection and MS mobile trajectory.

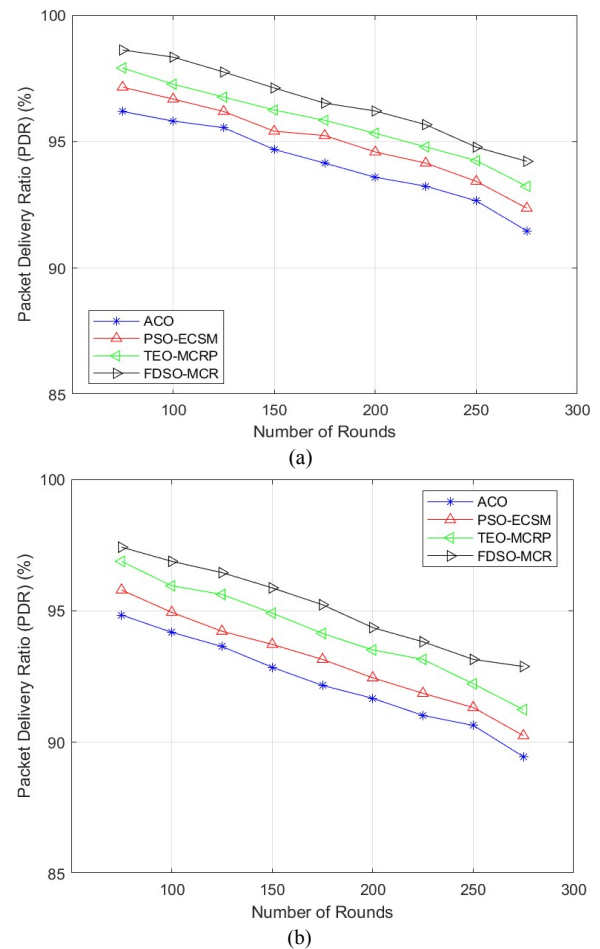
Figure 7 Packet delivery ratio (PDR) comparison vs. no. of nodes: (a) simulation model 1 (WSN1) and (b) simulation model 2 (WSN2) (see online version for colours)

Table 4 No. of packets received by BS among methods

Algorithms	Scenarios	
	WSN1	WSN2
ACO	589941	542548
PSO-ECSM	639480	608481
TEO-MCRP	658915	642465
FDSO-MCR	669802	658474

Sensitivity analysis reflects the robustness and flexibility of the protocol to diverse network parameters. A change in mobility rate at the sink side and nodes also affects WSNs in terms of performance; hence, the developed protocol is highly flexible. It provides greater mobility of sinks, making energy consumption by each node more or less equal. Further, it reduces the communication load

of far sensors, thus increasing the network lifetime. However, the protocol still achieves high mobility with possible latency, adapted by adaptive clustering and routing mechanisms. In addition, the protocol applies fuzzy logic and DSO to optimise the cluster and routing. This reduces the overhead of communication of data aggregation when the number of nodes is increased. All the results in varied configurations have been achieved with a high PDR and low energy consumption. Such adaptability ensures the protocol is suitable for dynamic real-world scenarios where network conditions frequently change. This sensitivity analysis highlights the protocol's ability to balance performance metrics under varying conditions, making it reliable and scalable. The protocol, through its proper handling of parameter variations, becomes a robust solution for different deployments of WSNs.

Table 5 PDR analysis vs. no. of nodes

No. of nodes	PDR (%)							
	WSN1				WSN2			
	ACO	PSO-ECSM	TEO-MCRP	FDSO-MCR	ACO	PSO-ECSM	TEO-MCRP	FDSO-MCR
100	96.19	97.15	97.91	98.62	94.84	95.79	96.88	97.42
150	95.81	96.68	97.27	98.34	94.18	94.94	95.95	96.88
200	95.55	96.19	96.76	97.75	93.64	94.22	95.62	96.45
250	94.69	95.41	96.25	97.12	92.85	93.72	94.91	95.87
300	94.15	95.24	95.84	96.52	92.16	93.15	94.14	95.23
350	93.59	94.59	95.33	96.21	91.67	92.45	93.51	94.36
400	93.24	94.15	94.79	95.67	91.02	91.86	93.15	93.82
450	92.66	93.43	94.25	94.78	90.64	91.32	92.22	93.15
500	91.47	92.36	93.23	94.22	89.45	90.28	91.24	92.87

- e *Analysis of the E2E delay:* In milliseconds, E2E delay is defined as the average amount of time required to route for packet transmission. The proposed system has been compared with existing node methods (100–500).

Figure 8 shows that in the results of all routing algorithms, the E2E delay increases when the number of nodes increases. It is concluded that the 100 nodes E2E delay are 24.26 ms, 19.95 ms, 14.65 ms, and 10.16 ms, employing methods such as ACO, PSO-ECSM, TEO-MCRP, and FDSO-MCR. ACO, PSO-ECSM, TEO-MCRP, and FDSO-MCR are observed to take 102.45 ms, 85.76 ms, 76.64 ms, and 65.81 ms in 500 nodes, respectively. The complete performance findings for E2E delay by routing techniques are displayed in Table 6.

Figures 4–8 show the results of all routing algorithms concerning Network lifetime, Energy Consumption, no. of packets received by BS, PDR, and E2E delay. These metrics have been measured by varying the number of nodes from 100–500. It is concluded that the 500 nodes, Network lifetime is 58485 rounds, Energy Consumption is 119.23 J,

no. of packets received by BS is 658474, PDR is 92.87% and E2E Delay of 65.81 ms by the proposed system.

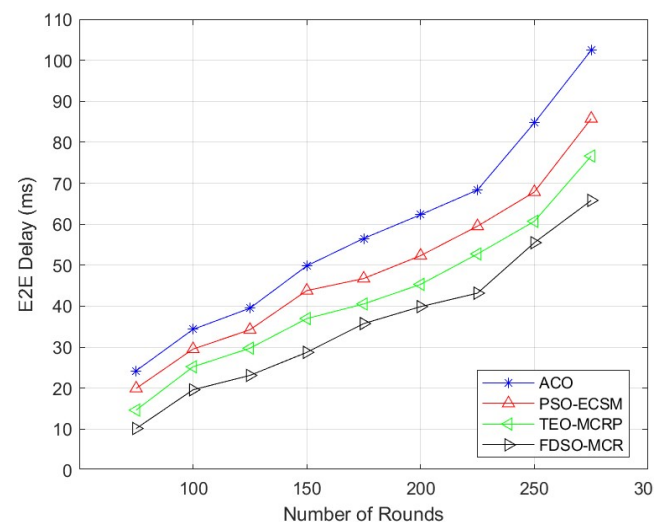
Figure 8 E2E delay comparison vs. no. of nodes (see online version for colours)

Table 6 Delay analysis vs. no. of nodes

No. of nodes	E2E delay (ms)			
	ACO	PSO-ECSM	TEO-MCRP	FDSO-MCR
100	24.26	19.95	14.65	10.16
150	34.35	29.54	25.22	19.61
200	39.51	34.25	29.75	23.12
250	49.85	43.81	36.98	28.74
300	56.54	46.75	40.55	35.76
350	62.32	52.33	45.32	39.89
400	68.35	59.52	52.74	43.18
450	84.74	67.86	60.71	55.49
500	102.45	85.76	76.64	65.81

DSO is chosen because it is very simple and converges very quickly. It is quite suitable for resource-constrained WSNs. PSO will suffer from premature convergence. ACO is computationally very expensive for optimising paths. So, DSO can be a good choice, keeping the exploration and exploitation function in proper balance. The algorithms, inspired by the foraging behaviour of doves, allow for dynamic optimisation and are decentralised, which fits perfectly into the distributed nature of WSNs. The low computational demands of DSO imply the network's low energy consumption, which is essentially required to prolong the network's lifetime. The algorithm performs fairly well adapting to dynamic environments; for instance, it will adjust with mobile sinks or variable node densities; therefore, it can achieve robust performance even with varying conditions. DSO is somewhat more scalable and less computationally intensive; hence, it suits the task at hand well- clustering and routing. Its ability to dynamically adjust solutions without much resource utilisation makes it a better option than other bio-inspired algorithms. This flexibility enhances the efficiency of the protocol. It ensures that the highest possible performance is achieved by this protocol across the given scenarios of networks, which further increases the basis for selecting DSO as the optimisation mechanism.

This section verifies the performance of the proposed FDSO-MCR method by presenting data clearly and in an orderly manner. Table 1 clearly shows simulation parameters, which form a strong reproducibility basis. The comparison in Table 3 shows the advantages of the proposed technique compared to other routing methods in terms of energy efficiency and lifetime of the network. However, to elaborate further on the content of this section, one may drill down to find the trends and correlations within the data. For instance, elaboration on the fact that parameters such as node density or mobility pattern affect FDSO-MCR with respect to other methods in terms of performance. Further discussion could involve statistical metrics such as standard deviation and confidence intervals that would further solidify the reliability of results in detail. The discussion could, therefore, better exemplify the real-world applicability of the proposed method by presenting

more explanations of results in the more practical scenarios of deployment. Overall, the results are comprehensive, but further elaborating on some critical trends would clarify them and make them more impactful.

5 Conclusion and future work

The conclusion is based on innovation and contribution using FDSO-MCR, thereby optimising heterogeneous WSN. Briefly, the implications towards energy efficiency, load balancing, and lifespan for the method are noted above; however, the perception with advancement in further details may take this conclusion even up to one or two grades, such as adaptability and larger scaling. Relevance to it would also be valuable in addressing future issues emerging within IoT-based WSNs, real-time processing, and in a multiple-sink environment. This can be an even more forward-looking account if it centres around future technology needs. Because relevance and lasting impression come out with good conclusions, it brings out FDSO-MCR and broader implications and applications. This paper proposes a novel clustering and routing scheme called fuzzy dove swarm optimisation mobile sink clustering routing (FDSO-MCR), which was introduced for heterogeneous WSNs. Dove foraging habits have been exploited to facilitate communication across WSN nodes. Determine the number of doves and then use the FDSO algorithm to deploy them on the CH solution. When choosing the CH in the network, the FDSO-MCR system is worked based on fitness criteria such as a node residual and average energy, distance to the MS, and the number of neighbour nodes.

Additionally, the proposed method uses a cluster of various fitness characteristics to identify the MS mobility path. To locate additional food, FDSO algorithm doves move toward the dove with the highest fitness of satiety. The objective function guides the selection of CH in WSN. Compared to existing approaches, simulation results show that the proposed approach increases network lifetime, reduced energy consumption, the amount of packets received by the BS, higher PDR, and lesser E2E delay. It reveals that the PDR for the proposed method is 92.88%, as opposed to the ACO, PSO-ECSM, and TEO-MCRP of 89.45%, 90.26%, and 91.24% by 500 nodes. Discussion of constraints has been minimal, which has provided an opportunity to improve: The study robustly explains the efficiency of the technique, FDSO-MCR, to optimum clustering and routing within the WSN. Some discussion on the constraints seems to be quite minimal while presenting potential constraints like calculations in very dense networks that will provide scalability or the efficiency of a method in high mobility environments. This shall not only prove the volume of the proposed method but also indicate what is yet to be improved in the future if these aspects are discussed; for example, if the extra computational overhead is debated to see how the FDSO-MCR shall deploy well in the resource-constraint environment, it adds practical value to this discussion; additionally, it can explain the energy

efficiency vs. latency tradeoff for real-time applications. Although the current representation underlines the strengths, the inclusions of limitations would render the study credible and, by all means, much more complete in providing an overall view of what the technique can do and what should be improved.

Future work will focus on developing several fault-aware techniques for massive networks with mobile sinks. This scope has occurred only passing over and hence would have added much stronger cohesion in addition to the conclusion. So, much more can be described further with insight into a forward-looking perspective; maybe at the forefront, there are advanced techniques either with analytical technique or maybe a developing hybrid optimisation method towards supporting FDSO-MCR modelling, which would further add to application possibly, to the prediction machine learning model cluster formation or dynamic sink positioning. Further research into combining the FDSO-MCR method with next-generation WSN applications, such as smart cities or industrial IoT, will make it highly applicable. Thus, this study will provide specific areas that require further research to make it significant, such as enhancement in security or energy harvesting techniques. This would give the research future scope in line with the trends and applications arising from technology, thus ensuring it is current and, in turn, has the necessary relevance and adaptation in today's WSN environment of the FDSO-MCR model. As laid out above, this further discussion would, in turn, make a more beneficial impact on and contribute to this research toward further work.

References

- Abinavkrishnaa, R., Raghuram, G., Varghese, A., Gowri, G.U. and Rahila, J. (2023) 'Scaling strategies for enhanced system performance: navigating stateful and stateless architectures', *FMDb Transactions on Sustainable Computer Letters*, Vol. 1, No. 4, pp.241–254.
- Anitha, K., Nagaraj, B.K., Paramasivan, P. and Shynu, T. (2023) 'Enhancing clustering performance with the rough set C-means algorithm', *FMDb Transactions on Sustainable Computing Systems*, Vol. 1, No. 4, pp.190–203.
- Aragani, V.M. (2024) 'Revolutionizing insurance through AI and data analytics: innovating policy underwriting and claims management for the digital era', *FMDb Transactions on Sustainable Computer Letters*, Vol. 2, No. 3, pp.176–185.
- Banala, S. (2024) 'Enhancing system stability with advanced techniques in site reliability engineering', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 2, pp.66–76.
- Boye, H. (2024) 'Strengthening cloud security through advanced encryption and anomaly detection techniques for secure data storage and transmission', *FMDb Transactions on Sustainable Computer Letters*, Vol. 2, No. 3, pp.153–163.
- Chundru, S. (2024) 'Harnessing the power of AI: revolutionizing metadata management with machine learning', *FMDb Transactions on Sustainable Computer Letters*, Vol. 2, No. 3, pp.164–175.
- Chunduri, V., Rajest, S.S., Allugunti, V.R., Verma, D., Aarthi, R. and Sharma, D.K. (2024) 'Deep neural network for brain tumour segmentation using guaranteed time slots (GTS) algorithm', *Advances in Computer and Electrical Engineering*, IGI Global, USA, pp.371–390.
- Darabkh, K.A., El-Yabroudi, M.Z. and El-Mousa, A.H. (2019) 'BPA-CRP: a balanced power-aware clustering and routing protocol for wireless sensor networks', *Ad Hoc Networks*, Vol. 82, No. 1, pp.155–171.
- Dhinakaran, P., Thinesh, M.A. and Paslavskyi, M. (2023) 'Enhancing cyber intrusion detection through ensemble learning: a comparison of bagging and stacking classifiers', *FMDb Transactions on Sustainable Computer Letters*, Vol. 1, No. 4, pp.210–227.
- Dhurgadevi, M. and Meenakshi Devi, P. (2018) 'An analysis of energy efficiency improvement through wireless energy transfer in wireless sensor network', *Wireless Personal Communications*, Vol. 98, No. 4, pp.3377–3391.
- Gandhi, M., Satheesh, C., Soji, E.S., Saranya, M., Rajest, S.S. and Kothuru, S.K. (2024) 'Image recognition and extraction on computerized vision for sign language decoding', *Explainable AI Applications for Human Behavior Analysis*, IGI Global, USA, pp.157–173.
- Harendharan, B. and Boussi Rahmouni, H. (2023) 'Evaluating the performance and impact of patient-centric and ambient sensors', *FMDb Transactions on Sustainable Computer Letters*, Vol. 1, No. 3, pp.192–201.
- He, X., Fu, X. and Yang, Y. (2019) 'Energy-efficient trajectory planning algorithm based on multi-objective PSO for the mobile sink in wireless sensor networks', *IEEE Access*, Vol. 7, No. 12, pp.176204–176217.
- Jasper, K.D., Jaishnav, M.N., Chowdhury, M.F., Badhan, R. and Sivakani, R. (2024) 'Defend and secure: a strategic and implementation framework for robust data breach prevention', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 1, pp.17–31.
- Jeba, J., Bose, S.R., Regin, R., Sudhan, M.B., Suman Rajest, S. and Babu, P.R. (2024) 'Efficient real-time Tamil character recognition via deep vision architecture', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 1, pp.1–16.
- Karthik, S., Bhaggiraj, S., Soji, E.S., Deve, L.S., Priscila, S.S. and Rajest, S.S. (2024) 'Real-time hand gesture recognition for stroke rehabilitation using deep learning approach', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 3, pp.157–172.
- Kaswan, A., Singh, V. and Jana, P.K. (2018) 'A multi-objective and pso based energy efficient path design for mobile sink in wireless sensor networks', *Pervasive and Mobile Computing*, Vol. 46, No. 6, pp.122–136.
- Khan, R.A. and Pathan, A.S.K. (2018) 'The state-of-the-art wireless body area sensor networks: a survey', *International Journal of Distributed Sensor Networks*, Vol. 14, No. 4, pp.1–23.
- Kooshari, A., Fartash, M., Mihanhezah, P., Chahardoli, M., Akbari Torkestani, J. and Nazari, S. (2023) 'An optimization method in wireless sensor network routing and IoT with water strider algorithm and ant colony optimization algorithm', *Evolutionary Intelligence*, Vol. 17, No. 4, pp.1527–1545.
- Kumar Nomula, V. (2023) 'A novel approach to analyzing medical sensor data using physiological models', *FMDb Transactions on Sustainable Health Science Letters*, Vol. 1, No. 4, pp.186–197.

- Kuppam, M., Godbole, M., Bammidi, T.R., Rajest, S.S. and Regin, R. (2024) 'Exploring innovative metrics to benchmark and ensure robustness in AI systems', *Explainable AI Applications for Human Behavior Analysis*, IGI Global, USA, pp.1–17.
- Lee, J.Y., Jung, K.D., Moon, S.J. and Jeong, H.Y. (2017) 'Improvement on LEACH protocol of a wide-area wireless sensor network', *Multimedia Tools and Applications*, Vol. 76, No. 7, pp.19843–19860.
- Licaj, B. and Karras, D.A. (2024) 'Integral smart vehicle automation framework using IoT, modern software, and infrastructure', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 3, pp.128–141.
- Minu, M.S., Subashka Ramesh, S.S., Canessane, R., Al-Amin, M. and Bin Sulaiman, R. (2023) 'Experimental analysis of UAV networks using oppositional glowworm swarm optimization and deep learning clustering and classification', *FMDB Transactions on Sustainable Computing Systems*, Vol. 1, No. 3, pp.124–134.
- Mohemed, R.E., Saleh, A.I., Abdelrazzak, M. and Samra, A.S. (2017) 'Energy-efficient routing protocols for solving energy hole problem in wireless sensor networks', *Computer Networks*, Vol. 114, No. 1, pp.51–66.
- Mostafaei, H. (2019) 'Energy-efficient algorithm for reliable routing of wireless sensor networks', *IEEE Transactions on Industrial Electronics*, Vol. 66, No. 7, pp.5567–5575.
- Musale, V. and Chaudhari, D. (2017) 'Challenges, protocols and case studies in design of reliable energy efficient wireless sensor networks', *2017 4th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, pp.1–7.
- Nanban, D., Ajitha, Y., Selvan, J., Pierre, T.J., Sara, S.B.V.J. and Ragesha, R. (2024) 'Enhancing user experience in air canvas through robust hand gesture recognition using computer vision', *FMDB Transactions on Sustainable Computer Letters*, Vol. 2, No. 3, pp.131–143.
- Nanban, D., Selvan, J., Christus, A.T.A. and Amin, M.A. (2024) 'Enhancing air traffic management: the transformative role of artificial intelligence in modern air traffic control', *FMDB Transactions on Sustainable Intelligent Networks*, Vol. 1, No. 2, pp.72–84.
- Nandi, A., Sonowal, B., Rabha, D. and Vaibhav, A. (2019) 'Centered Sink LEACH protocol for enhanced performance of wireless sensor network', *2019 International Conference on Automation, Computational and Technology Management (ICACTM)*, London, U.K., pp.436–440.
- Nayak, P., Swetha, G.K., Gupta, S. and Madhavi, K. (2021) 'Routing in wireless sensor networks using machine learning techniques: challenges and opportunities', *Measurement*, Vol. 178, No. 1, pp.1–15.
- Paramasivan, P., Rajest, S.S., Chinnusamy, K., Regin, R. and John Joseph, F.J. (2024) *Cross-Industry AI Applications. Advances in Computational Intelligence and Robotics*, IGI, USA, DOI: 10.4018/979-8-3693-5951-8.
- Parveen Roja, M., Kuppam, M., Koduru, S.K.R., Byloppilly, R., Trivedi, S.D. and Rajest, S.S. (2024) *An Aid of Business Intelligence in Retailing Services and Experience Using Artificial Intelligence. Cross-Industry AI Applications*, IGI Global, USA, pp.14–30.
- Pranav, R.P., Prawin, R.P., Paramasivan, P., Shynu, T. and Subhashni, R. (2024) 'IoT-secNet: A trust-based framework for enhancing security in IoT communications and network layer protocols', *FMDB Transactions on Sustainable Computing Systems*, Vol. 2, No. 2, pp.96–106.
- Raj, M.A., Thinesh, M.A., Varmann, S.S.M., Pothu, A.R. and Paramasivan, P. (2024) 'Ensemble-based phishing website detection using extra trees classifier', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 3, pp.142–156.
- Raja, A.S.V., Jasper, K.D., Poornima, V., Priscila, S.S., Thenmozhi, A. and Ratkovic, N. (2024) 'Tech horizons unveiled: navigating the transformative decade in AIML, cybersecurity, IoT, gaming, and data science education', *FMDB Transactions on Sustainable Intelligent Networks*, Vol. 1, No. 2, pp.120–134.
- Rajasekaran, N., Jagatheesan, S.M., Krithika, S. and Albanchez, J.S. (2023) 'Development and testing of incorporated ASM with MVP architecture model for android mobile app development', *FMDB Transactions on Sustainable Computing Systems*, Vol. 1, No. 2, pp.65–76.
- Rajest, S.S., Moccia, S., Singh, B., Regin, R. and Jeganathan, J. (Eds.) (2024) 'Advancing intelligent networks through distributed optimization', *Advances in Computer and Electrical Engineering*, IGI Global, USA, DOI: 10.4018/979-8-3693-3739-4.
- Sahoo, B.M., Amgoth, T. and Pandey, H.M. (2020) 'Particle swarm optimization based energy efficient clustering and sink mobility in heterogeneous wireless sensor network', *Ad Hoc Networks*, Vol. 106, No. 9, pp.1–28.
- Sajini, S., Reddi, L.T., Regin, R. and Rajest, S.S. (2023) 'A comparative analysis of routing protocols for efficient data transmission in vehicular ad hoc networks (VANETs)', *FMDB Transactions on Sustainable Computing Systems*, Vol. 1, No. 1, pp.1–10.
- Sayedelahl, M.A. and Farouk, R.M. (2024) 'Hybrid approach to image segmentation with artificial neural networks and gabor wavelets', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 2, pp.77–90.
- Shalom Soji, E., Gnanamalar, S., Arumugam, N., Priscila, S.S., Selvam, N. and Rajest, S.S. (2024) 'AI-driven computer vision for intelligent home automation and surveillance systems', *Explainable AI Applications for Human Behavior Analysis*, IGI Global, USA, pp.242–257.
- Soji, E.S., Karthik, S., Priscila, S.S., Gnanaguru, G., Rajest, S.S. and Sebastian, A. (2024a) 'Optimizing e-voting systems with a targeted implementation of the STAP protocol', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 2, pp.91–105.
- Soji, E.S., Karthik, S., Priscila, S.S., Hanirex, D.K., Rajest, S.S. and Sebastian, A. (2024b) 'Designing an E-voting system architecture using the STAP protocol', *FMDB Transactions on Sustainable Intelligent Networks*, Vol. 1, No. 2, pp.96–109.
- Srilakshmi, U., Sandhya, I., Manikandan, J., Bindu, A.H., Regin, R. and Rajest, S.S. (2024) 'Design and implementation of energy-efficient protocols for underwater wireless sensor networks', *Advances in Computer and Electrical Engineering*, IGI Global, USA, pp.417–430.
- Su, M.C., Chen, J.H., Utami, A.M., Lin, S.C. and Wei, H.H. (2022) *Dove Swarm Optimization Algorithm. IEEE Access*, Vol. 10, No. 4, pp.46690–46696.
- Sun, G., Zhao, X., Shen, G., Liu, Y., Wang, A., Jayaprakasam, S., Zhang, Y. and Leung, V.C. (2020) 'Improving performance of distributed collaborative beamforming in mobile wireless sensor networks: a multi-objective optimization method', *IEEE Internet of Things Journal*, Vol. 7, No. 8, pp.6787–6801.

- Sundararajan, V., Steffi, R. and Shynu, T. (2023) 'Data fusion strategies for collaborative multi-sensor systems: achieving enhanced observational accuracy and resilience', *FMDB Transactions on Sustainable Computing Systems*, Vol. 1, No. 3, pp.112–123.
- Tabibi, S. and Ghaffari, A. (2019) 'Energy-efficient routing mechanism for mobile sink in wireless sensor networks using particle swarm optimization algorithm', *Wireless Personal Communications*, Vol. 104, No. 9, pp.199–216.
- Thirunagalingam, A. (2024) 'Transforming real-time data processing: the impact of AutoML on dynamic data pipelines', *FMDB Transactions on Sustainable Intelligent Networks*, Vol. 1, No. 2, pp.110–119.
- Thomson, C., Wadhaj, I., Tan, Z. and Al-Dubai, A. (2021) 'Towards an energy balancing solution for wireless sensor network with mobile sink node', *Computer Communications*, Vol. 170, No. 1, pp.50–64.
- Usman, M. and Ullah, A. (2024) 'Blockchain technology implementation in libraries: an overview of potential benefits and challenges', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 1, pp.42–53.
- Venkat Narayan, S., Vignesh Raja, A.S., Priya Rajasri, A.M., Shakywar, P. and Shynu, T. (2023) 'Forging collective cognitive excellence: the role of innovative technologies in collaborative editing platforms', *FMDB Transactions on Sustainable Computer Letters*, Vol. 1, No. 4, pp.267–281.
- Verma, S., Sood, N. and Sharma, A.K. (2018) 'Design of a novel routing architecture for harsh environment monitoring in heterogeneous WSN', *IET Wireless Sensor Systems*, Vol. 8, No. 6, pp.284–294.
- Vignesh Raja, A.S., Jasper, K.D., Aljaafreh, R., Yogeshwaran, S.K. and Saleem, M. (2023) 'A comprehensive exploration of blockchain-based decentralized applications and federated learning in reshaping data management', *FMDB Transactions on Sustainable Computer Letters*, Vol. 1, No. 4, pp.228–240.
- Vijayalakshmi, K. and Anandan, P. (2019) 'A multi-objective tabu particle swarm optimization for effective cluster head selection in WSN', *Cluster Computing*, Vol. 22, No. S5, pp.12275–12282.
- Vijayashree, R. and Suresh Ghana Dhas, C. (2019) 'Energy efficient data collection with multiple mobile sink using artificial bee colony algorithm in large-scale WSN', *Automatika*, Vol. 60, No. 5, pp.555–563.
- Wang, J., Cao, J., Sherratt, R.S. and Park, J.H. (2018) 'An improved ant colony optimization-based approach with mobile sink for wireless sensor networks', *Journal of Supercomputing*, Vol. 74, No. 12, pp.6633–6645.
- Wen, W., Zhao, S., Shang, C. and Chang, C.Y. (2017) 'EAPC: energy-aware path construction for data collection using mobile sink in wireless sensor networks', *IEEE Sensors Journal*, Vol. 18, No. 2, pp.890–901.
- Yalçın, S. and Erdem, E. (2020) 'A mobile sink path planning for wireless sensor networks based on priority-ordered dependent nonparametric trees', *International Journal of Communication Systems*, Vol. 33, No. 12, pp.1–19.
- Yalçın, S. and Erdem, E. (2022) 'BTA-MM: burst traffic awareness-based adaptive mobility model with mobile sinks for heterogeneous wireless sensor networks', *ISA Transactions*, Vol. 125, No. 6, pp.338–359.
- Yalçın, S. and Erdem, E. (2022) 'TEO-MCRP: thermal exchange optimization-based clustering routing protocol with a mobile sink for wireless sensor networks', *Journal of King Saud University-Computer and Information Sciences*, Vol. 34, No. 8, pp.5333–5348.
- Zanardo, E. (2024a) 'Chronostamp: A general-purpose run-time for data-flow computing in a distributed environment', *AVE Trends in Intelligent Computing Systems*, Vol. 1, No. 2, pp.106–115.
- Zanardo, E. (2024b) 'Functional language for fault-tolerant distributed computing with cooperative task farming', *FMDB Transactions on Sustainable Computer Letters*, Vol. 2, No. 3, pp.144–152.
- Zhang, T. and Zhang, J. (2018) 'A kind of effective data aggregating method based on compressive sensing for wireless sensor network', *EURASIP Journal on Wireless Communications and Networking*, Vol. 15, No. 9, pp.1–15.