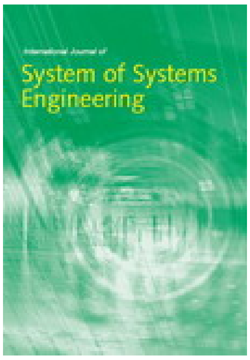


International Journal of System of Systems Engineering

ISSN online: 1748-068X - ISSN print: 1748-0671
https://www.inderscience.com/ijsse

Wireless sensor network data gathering using a multi-fold gravitational search algorithm with a mobile agent

R. Saravanan, V. Sathya

DOI: 10.1504/IJSSE.2024.10054554

Article History:

Received:	13 October 2022
Last revised:	03 December 2022
Accepted:	06 December 2022
Published online:	09 January 2024

Wireless sensor network data gathering using a multi-fold gravitational search algorithm with a mobile agent

R. Saravanan*

Department of Computer Applications,
IFIM College, Electronic City,
Bengaluru, 560100, Karnataka, India
Email: saraoffivlr@gmail.com
*Corresponding author

V. Sathya

Department of Computer Applications,
MGR College,
Hosur, 635109, Tamil Nadu, India
Email: sathya.mca@adhiyamaan.in

Abstract: Wireless sensor network (WSN) communications fascinate researchers. WSN uses affordable sensor nodes to deliver data wirelessly to a base station, reducing sensor node energy and transmission costs. MWCSGA is well-tested, and NS-2 is used to evaluate CSOGA's performance. GA-LEACH and MW-LEACH measure work performance alongside CSOGA. Simulating multiple circumstances test the methods of TCL, C++, and Ns2. Live mode (NAM), animated with tracking files, monitors performance based on parameters and values. Energy, latency, packet, speed, and delivery ratio are metrics. This study shows how an IOT WSN can use a mobile agent and the multi-fold gravitational search method (MFGSA). The gravitational search algorithm (GSA) chooses the cluster head (CH) and optimises the MA path to sensor nodes. Cluster head optimisation included node energy, BS transmission costs, and neighbouring nodes with emergency data. Clustering allocated MA source nodes, and GSA optimised the path. Compare the suggested method's network efficiency and longevity to older ones. GSA-based MA itinerary planning is compared to task energy consumption methods. The novel method improves MA success, network stability, and energy use.

Keywords: WSN; wireless sensor network; data collection; MFGSA; multi-fold gravitational search algorithm; CH selection; mobile agent; network lifetime.

Reference to this paper should be made as follows: Saravanan, R. and Sathya, V. (2024) 'Wireless sensor network data gathering using a multi-fold gravitational search algorithm with a mobile agent', *Int. J. System of Systems Engineering*, Vol. 14, No. 1, pp.23–41.

Biographical notes: R. Saravanan received his BSc in Computer Science from Madras University in 2004. He received his MCA from Anna University in 2008 and his MPhil from Periyar University in 2013. Currently, He is working as Assistant Professor at IFIM College, Karnataka, India. He has published

more than 15 research papers in various international journals. He has participated in various national and international conferences, workshops, and seminars. He has 12 years of teaching experience on both undergraduate and graduate levels. His area of interest includes wireless sensor networks, artificial intelligence, and data science.

V. Sathya received her BSc in Computer Science from Bharathidasan University, an MCA from Bharathidasan University, and a PhD from Anna University. She is currently working as an Assistant Professor at MGR College, Hosur. She has 15 years of experience in the teaching field. She has done her research on Web Semantic. She has published in more than 32 journals in various international journals. She has participated in various national and international conferences, workshops, and seminars. Her area of interest includes web semantics, artificial intelligence, neural network, machine learning, and wireless sensor networks.

1 Introduction

Small sensor nodes are spread out over an area to create wireless sensor networks (WSNs), which track constantly changing physical phenomena such as humidity, pressure, and temperature. WSNs are used for a range of applications in the fields of engineering, medicine, agriculture, and surveillance monitoring. Additionally, they may be used in typical outdoor, indoor, underwater, underground, and landscape settings, making them more balanced. A WSN is a collection of many low-cost sensor nodes that are densely placed in the field to gather data and wirelessly transit to the BS. Only sending the most important data from the sensor field to the sink must be transmitted since communication consumes more energy than any other process in a sensor node. A large area of research in WSN is data gathering. Intending to decrease the communication overhead and power expenditure of sensor nodes throughout the data collection process in WSNs, data collection is a highly significant approach. Different methods can be used to acquire data.

Since there has been a sizable amount of study on slight network models, because the reprogrammed edges that the WS model brought to the dynamic model could result in separated nodes (Sajedi et al., 2022), a paradigm with additional shortcut edges was developed by Yun and Yoo (2021). They avoided the risk of isolating nodes by substituting random edge addition for random reconnection. Karunanithy and Velusamy (2020) investigated the Laplacian operator on 'small-world' lattices, which is crucial to the spread of knowledge. A direct good wireless model was created to optimise the network to address the issue of redundancies and low network efficiency. It could be used successfully to research the spread of infectious diseases and the distribution of community knowledge (Osamy et al., 2021). These models place the small-world phenomena in the middle of the regular and unpredictable network structures and have looked at the mechanisms that cause small-world networks to evolve. Typically, sensor nodes are placed wherever they are needed. To gather the data from the surroundings, they collaborate and work dispersedly. Sensor nodes have data-collecting capabilities that may be used in various ways to collect data. This research paper examines all conceivable data collection algorithm issues for real-time WSN applications. It suggests a feasible data collection technique that can provide data securely to the BS without delay or collision while using little energy. Data gathering is one of the main roles of sensor nodes.

Normally, the sensors gather environmental data with send it to the BS or sink node. The frequency and quantity of sensors that convey the specific application determine data. To eliminate duplicate transmission and process the data about the perceived environment, data collection is clear as collecting data from many sensors and sending the aggregated information to the BS. Integrating sensed data into high-quality information is necessary for data collecting. It incorporates data-collecting algorithms that gather perceived information from several sensors and send it to additional processing. Data collecting involves some open research topics with dual aims, such as lowering energy use while increasing speed, increasing accuracy while minimising energy, and so on. So, as a first step, our research focuses on maximising the usage of energy resources throughout the network's clustering process and lowering the latency for the priority event packets. The second area of our research focuses on streamlining allocating sources to mobile agents. The structure of the paper is as follows: In Section 2, the background of the study is explained. In Section 3, the statement of the problem is described. The proposed methodology is briefly described in Section 4, followed by algorithms. Section 5 is followed by a conclusion.

2 Background

By offering an analysis of various data collection methodologies and algorithms, the most current improvements in data collection approaches for WSN about terrestrial, subsurface, and underwater locations are covered (Wei et al., 2021). Various characteristics, including energy efficiency, collection rate, network longevity, amount of living nodes, and throughput, were used to analyse, examine, and categorise data collection systems into Flat networks and Hierarchical Networks (Maivizhi and Yogesh, 2021). A thorough comparison of the zone-based energy-aware (ZEAL) and maximum amount shortest path (MASP) DC protocols are provided to aid researchers in choosing the appropriate majority algorithm for a WSN application (Ajmi et al., 2021; Sarode et al., 2021). ETDMAGA, a GA-based method, is used for effective scheduling to reduce data collection delay (Saranraj et al., 2022). The membership value of an element indicates how much it is a part of a set (Amrani et al., 2021; Grigoryan and Collins, 2021; Gupta et al., 2022). The parent node has the lowest total weight as a consequence (Kalaikumar and Baburaj, 2020; Osamy et al., 2020). To overcome the problem of hot spots, the WSN is configured into clusters of different sizes (Sajedi et al., 2022). Choosing the task nodes for each work cycle is the initial step in making data predictions (Raj et al., 2020). During the broad search stage of the Intelligent DC Technique, a novel crossover operation is employed the Bees algorithm is used and modified (Sadeghi and Avokh, 2020).

The recently created stochastic optimisation algorithm known as the gravitational search algorithm (GSA) is based on the laws of gravity and mass interactions. In contrast to other well-known society optimisation methods inspired by swarm behaviours, the search agents in this methodology are a group of masses that interact with one another based on Newtonian gravity and the laws of motion. Investigators are treated as objects in GSA, and their masses determine their function. Gravity acts as an attractive force between all objects, moving them collectively in the direction of items with heavier weights. The heavy masses match up with effective remedies to the issue. To put it another way, each mass provides an answer, and the algorithm is run by correctly altering the gravitational and inertia masses.

The integrated grid clustering and monkey tree search (MTS) behavioural model is designed to optimise WSN lifespan and to assure data collection with minimal energy consumption for distributed WSNs (Cao et al., 2020). Tree topology with movable edge nodes is presented to improve the performance and longevity of the WSN Cluster-Tree-based technique (Karunanithy and Velusamy, 2020; Mohanty et al., 2020; Ghaderi et al., 2020). The optimum CH for each cluster is found using an improved energy-conscious cuckoo search method (Osamy et al., 2021a; Osamy et al., 2021b). GTBRP and the modified ACO-based algorithm (Pour et al., 2022; Wijesinghe et al., 2022); (Dewan et al., 2022) are both used to provide the best efficient path for sink nodes to improve the trade-off between transmission delay and power usage in the WSN (Bhushan et al., 2021). The CH work may be rotated round-by-round across different sensors thanks to the cuckoo-search algorithm (Osamy et al., 2021a). Scheduling the nodes to get valuable sensor data is done using query ordering and data collection methods (Faris et al., 2021). The plan employs a Query Order model that ranks queries according to performance and latency. It enhances the extreme learning machine's hidden layer bias and input weight matrix (Lyu et al., 2020; Soundari and Jyothi, 2020). The query order is framed, and the frames are then rated using a multi-objective function (Borham et al., 2021).

Frameworks for long-term monitoring applications such as spatiotemporal approximate DC (STAC) and adaptive routing algorithm for in-network collection (RINA) use the least amount of information possible as residual energy, node distance, and connection power to create a routing tree. To increase the energy efficiency of the network's communication process, the multi weight chicken swarm based genetic algorithm for energy efficient clustering (MWCSGA) algorithm was created (Dehkordi et al., 2020); (Basha and Yaashuwanth, 2019). A periodic multi-node charging and data-gathering method using a mobile device provides an everlasting network service (MD). The network is divided into numerous cells, and the MD cycles through each cell to collect data and recharge the nodes to increase the amount of data generated per unit of energy used by the MD (Seyfollahi and Ghaffari, 2020). FGAF-CDG, deep learning based data mining (DDM) model is utilised to produce energy savings and effective load balancing, which is a fuzzy-oriented geographic routing algorithm (Sanjay Gandhi et al., 2020; Liu et al., 2020; Sarode and Reshmi, 2020). The problem and possible alternatives have been found by analysing the current models regarding the goals of data aggregation, the nature of the algorithms, topology, and interference model, the kind of applications, the collection delay, and the collection function. The primary goals of the research are to investigate and evaluate energy-efficient clustering schemes and mobile agent-based data collection schemes for WSNs, to develop the multi-fold gravitational search algorithm (MFGSA), which employs MA for data collection, and to put into practice the suggested emergency traffic-aware energy-efficient clustering mechanism assisted by Mobile Agent based data gathering mechanism.

3 Problem statement

The lifetime of nodes, network stability, energy consumption, and success rate provides the biggest obstacles to data gathering in WSNs. Power consumption is a main concern in the static sink strategy as the sink node is static. In such circumstances, the network life span is similarly shortened. This issue may be solved by adopting a mobile sink strategy for data collection. The lifespan of the node is decreased in this manner since the sink is mobile. Utilising mobile mules for data gathering is a critical component of mobility-based approaches. These techniques are applied in networks among sparse sensors. We can enlarge the number of packets captured using many mobile mules for data collection. The main concern in data collecting is network stability. A good data storage method can also improve the quality of packets gathered. Networks employ tree and mesh topologies. Because mesh topology allows for more packet exchanges than tree topology, which only allows for packet exchanges between parent and child nodes, mesh topology can lead to reduced quality and more successful packet collection. The node's lifetime, network stability, energy consumption, and success rate were some of the issues we concentrated on in this research paper as we discussed various methods to address them. Next, we compared various data aggregation techniques based on these issues, including the node's lifetime, network stability, energy consumption, and success rate.

4 Proposed methodology

The proposed multifold gravitational search optimisation-based clustering algorithm clusters the nodes, choose an ideal cluster head from among them, takes the data from the sensor nodes and, via MA (MA, transfers it to a server or BS. In the multifold GSA, the cluster head selection process was optimised using GSA in the first instance, and the MA travel path for data collection for each node was optimised in the second. Data collection on or after group members toward CHand data transmission since CH to BS through MAs is dealt with during the algorithm's stable phase. The method also handles the choice of CH and cluster development. The used symbols are specified in Table 1.

4.1 Setup phase

Each node initially has an equal chance of becoming the cluster head (*p*), which makes all nodes eligible to hold this position. The conventional clustering procedure LEACH defines equal probability. Two nodes with the same probability, nevertheless, could have distinct properties. As a result, the GSA-defined acceleration parameter has modified the probability '*p*' in the suggested algorithm.

4.1.1 Using GSA to choose the best cluster head

Every eligible node that has the potential to become a cluster head functions as an agent in GSA. As a result, we have '*N*' agents in the GSA setup phase in a network with '*N*' randomly dispersed nodes in an '*M*×*M*' sq. The second rule specifies the acceleration that the particle experiences due to the force of the particle acting on it and its mass. According to the first law, there is a certain amount of gravitational force between each particle and every other particle.

Table 1 Symbols and notations used

p	Probability of a node being the head of a cluster
N	Network nodes
$M \times M$	Network size
X_{i^d}	Location of *i*th node
E_{B_i}	Data that is normal or emergency in bit value
Nei_i	Neighbour of *i*th node
k	Number of a node's neighbours
E_i	Energy of the *i*th node
F_{i,j^d}	Gravitational force
em	Nodes having emergency data as a percentage
CH_i	Cluster head set for *i*th node
L	Size of packet
FMMA	Free memory of mobile agent

When the rule is applied to the sensor, every node 'Ni' must draw 'Nj' adjacent. The force $F_{i,j^d}(t)$ performing in the *d*th measurement with which the node 'Nj' pull otherwise, push 'Ni' at whichever agreed time '*t*' is given as follows:

$$F_{i,j^d}(t) = G\frac{M_{pi}(t).M_{aj}(t)}{D_{i,j}(t)}(X_{i^d}(t) - X_{i^d}(t) \tag{1}$$

where G denotes the gravitational constant, M_{pi} denotes the node 'Ni' passive gravitational mass, M_{aj} denotes the node *Nj* active gravitational mass, $X_{i^d}(t)$ denotes the positions of the nodes 'Nj' and 'Ni', and $D_{i,j}(t)$ denote the Euclidean distance between the nodes. The nodes will exert force on their neighbours in two dimensions since the network is two-dimensional, leading to:

$$F^{x}{}_{i,j}(t) = G\frac{M_{pi}(t) * M_{aj}(t)}{D_{i,j}(t)}(X_j(t) - X_i(t)) \tag{2}$$

$$F^{y}{}_{i,j}(t) = G\frac{M_{pi}(t) * M_{aj}(t)}{D_{i,j}(t)}(Y_j(t) - Y_i(t)) \tag{3}$$

where $F^{x}{}_{i,j}(t)$ and $F^{y}{}_{i,j}(t)$ indicates the force applied on the node in the X and Y dimensions. Given that a node has k neighbours, each of these neighbours will exert a force on the node 'Ni', resulting in a sum of all the forces that is arbitrarily weighted and may be calculated as follows:

$$F_i^d(t) = \sum_{j=1, j \neq i}^{k} rand_j * F^{d}{}_{i,j}(t) \tag{4}$$

where $rand_j$ in the range of (0, 1). The nodes' gravitational masses are calculated as follows:

$$M_{pi} = M_{aj} = \frac{m_i(t)}{\sum_{j=1}^{k} m_j(t)} \tag{5}$$

Such that

$$m_i(t) = \frac{fit_i - worst(t)}{best(t) - worst(t)} \tag{6}$$

where fit_i is the fitness function of the *i*th node; when the minimisation problem is considered, the worst value of a node's fitness function in the region of '*k*' neighbours is found, whereas the maximisation problem does the reverse. As a result, we have the maximising problem

$$best(t) = \max\{fit_j(t)\}\ j \in \{1, 2, \ldots, k\} \tag{7}$$

$$worst(t) = \min\{fit_j(t)\}\ \mathrm{j} \in \{1, 2, \ldots, k\} \tag{8}$$

The nodes' fitness function depends on the three sub-routines or three sub-fitness functions listed below:

4.1.2 Amount of nearby emergency nodes

The number of adjacent nodes that relay emergency data to the BS determines the first sub-fitness factor. If a node with greater emergency data (ED) neighbours is selected as CH, the likelihood of ED being lost from the network is greatly reduced. This allows additional nodes having data transmissions to relay data to the cluster head over a small range than if they were in direct communication with the BS and the distance was considerably higher. As a result, the fitness function is determined as follows:

$$fit_i^{emergency} = \frac{\sum \frac{Nei_i}{E_{BNei_i}} = 1}{em * N} \tag{9}$$

4.1.3 Remaining energy of the node

The remaining energy of a node that has created a cluster in which the greater part of the cluster members contain ED must also be on the upper side to safely convey data to the BS. The low-energy cluster head will lose all the data it has collected if the reverse happens. The fitness function is now,

$$fit_i^{energy} = \frac{residual\,energy}{E_i} \tag{10}$$

4.1.4 Communication cost

Another crucial variable must be considered for the best cluster head election. This parameter specifies the quantity of energy required by cluster members to send data to the cluster head, direct communication cost, and the cost of sending data to the BS, or intra-cluster communication cost. The network's performance will suffer since it cannot afford additional communication costs. Reduced communication costs are required. The fitness function is therefore calculated as follows:

$$fit_i^{cost} = \frac{\sum_{j=1}^{k}(E_{elec} * L * E_{fs} * L * D * D_{i,j}^2)}{\sum_{j=1}^{k}(Nei_j * E_j)} + \frac{(E_{elec} * L * E_{fs} * L * D_{i,BS}^2}{Ei} \tag{11}$$

As a result, the node's final fitness function is,

$$fit_i = \alpha * fit_i^{emergency} + \beta * fit_i^{energy} + \gamma * (1 - fit_i^{cost}) \tag{12}$$

where the sum of α, β, γ are equal to 1, the node that has created a cluster with a greater number of neighbours with emergency data, has more energy left in it and has a lower energy cost for communication would be the ideal cluster leader. Following the computation of the masses, the acceleration may be calculated as follows:

$$acc_i^d = \frac{F_i^d(t)}{M_i(t)} \tag{13}$$

Higher mass nodes often experience the least acceleration and are regarded as fit. As a result, the likelihood 'p' that would befall the CH is modified as follows:

$$p_{adj} = \frac{p_i}{acc_i^d} \tag{14}$$

Every node creates a random quantity after accounting for its nodes' probability and then compares it to a threshold value. The node becomes the cluster leader for the existing round if the random number is smaller than the threshold value and has not already held that position for the previous '1/p' rounds.

$$Th(i) = \left\{ \begin{array}{ll} \dfrac{p_{adj}(r_i)}{1 - p_{adj}(r)(r - mod \dfrac{1}{p_{adj}(r)})} ; & \text{if node}(i) \in G(r) \\ 0; & \text{otherwise} \end{array} \right\} \tag{15}$$

The advertisement packet was sent to all the elected cluster leaders' neighbours within their communication range. After receiving the packet, Every node in the area can join the CH and form a cluster through them. Though, a node may get the announcement packet beginning many CH. In this case, the cluster head with the lowest distance variation is the one the nodes join.

4.2 Steady phase

The BS, cluster heads, and cluster members carry out the data transmission. Following cluster creation, the CH broadcasts a Time Division Multiple Access schedules for data transmission to the member nodes. Each cluster member aggregates the sensed data at their respective CH during the specified periods for measuring. After collecting it from cluster members, the CH must transmit data to the BS. The MAs have been used to acquire data from the CH for this reason. The most crucial phase is planning the schedule for the mobile agent, which will specify the order of the CH visits MA will make to collect data from them. The suggested technique applies GSA a second time to choose the ideal route for the MA.

4.2.1 Using GSA to organise MA's travels in the most efficient way

The numeral of MAs intended for a given amount of source nodes, as well as the allowance of the source nodes to the MA, must be calculated to optimise the MA itinerary.

4.2.2 Deciding the number of MAs

The amount of free RAM on the MA and the total amount of data to be gathered determine the number of MAs needed for data collection in this stage. In math, it is calculated as:

$$RMA = \frac{\sum_{i=1}^{p} L_{CH_i}}{FMMA} \tag{16}$$

where L_{CH_i} is the data packet size with the ith cluster head, and RMA is the needed number of MA(source node). Let $MA = \{MA_1, MA_2, \ldots, MA_{RMA}\}$ RMA represent the group of MAs gathering data from the number of cluster heads. As a result, each MA will receive a cluster head with a $\frac{p}{RMA}$ number.

4.2.3 Allowing MAs accessibility to the source nodes

The proposed distribution technique, the k-means clustering algorithm, is initially given a random source node as an input to create 'RMA' clusters. The closest node to the source node that was randomly selected forms a cluster. Another node is added to the cluster in the following iteration, which is situated neighbouring the cluster's centroid. The iteration continues as long as the cluster's member count does not exceed p/RMA. As a result, the source nodes may be assigned to the MA in a distance-efficient manner using the k-means clustering method. At the end of this phase, each MA will meet with a group of cluster heads, and its itinerary is indicated by:

$$I_{MA} = \left\{ CH_1, CH_2, \ldots, CH_{\frac{\rho}{RMA}} \right\} \tag{17}$$

4.2.4 Optimal itinerary planning for MA

The GSA algorithm is used to organise the itinerary for collecting/RMA source nodes. As previously stated, the agent with less acceleration is thought to be more effective. In this stage, the fitness functions previously established for the best cluster head selection are modified. Still, the remainder of the calculation for masses and gravitational force is left unchanged. Once more, the priority for the MA to visit the nodes has to be maximised in this maximisation problem. The next three sub-routines or sub-fitness functions are described, affecting the fitness function of the source nodes.

The data type for the node: A node's emergency data must be forwarded toward the BS with higher priority than other nodes' normal data since it may include emergency information. As a result, the fitness function is assessed using the node's EB i value. This needs to be improved upon.

$$fit_i^{data-type} = E_{B_I} \tag{18}$$

Node's energy: Nodes with emergency data are given extra priority over nodes with regular data. However, the nodes with emergency data that have the least amount of energy left in them or require more energy to communicate with the BS are given precedence. As a result, this fitness function includes both the node's remaining energy and the energy used in communicating with the BS.

$$fit_i^{energy} = \frac{E_{elec} * L + E_{fs} * L * D_{i,BS}^2}{E_i} \tag{19}$$

Distance with the BS: The MA has a higher priority to visit a node as soon as feasible if it is far from the BS and has emergency data and little remaining energy. As a result, the node's distance from the BS influences this fitness function.

$$fit_i^{distance} = \sqrt{(X1 - BX)^2 + (Y1 - BY)^2} \tag{20}$$

where the BS's coordinates are BX and BY, and the node's coordinates are X1 and Y1, respectively. The node will receive more priority for visits if the distance is greater. In order to calculate the final fitness function below.

$$fit_i = \alpha * fit_i^{data-type} + \beta * fit_i^{energy} + \gamma * fit_i^{distance} \tag{21}$$

where sum of α , β, γ are equal to 1, after calculating each node's fitness function, the force applied to the node, its mass, and its acceleration is calculated. The MA travels to the node with the lowest acceleration first, followed by the node with the highest acceleration. This concludes the stable phase and the current round. The procedure is followed again at the start of the subsequent cycle, and selection of CH is selected to distribute the workload among them. The pseudocode for the multi-fold gravitational search algorithm is specified in Algorithm 1.

Algorithm 1 Pseudocode for multi-fold gravitational search algorithm

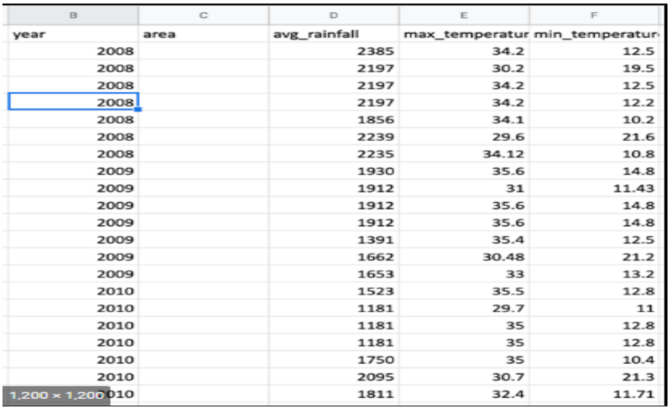
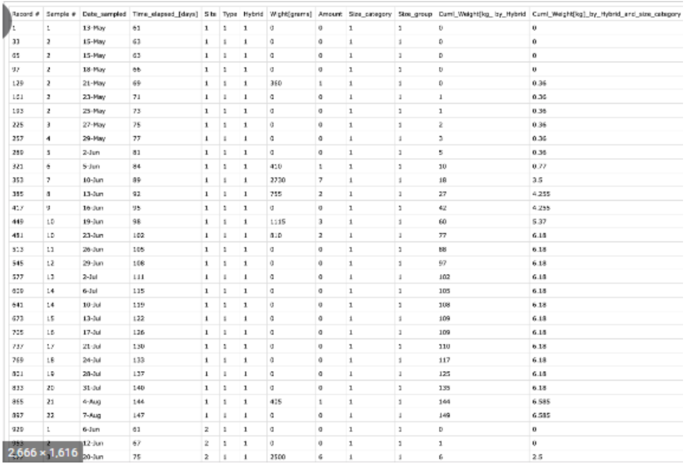
```
                        Input: Agriculture data
                            Output: Collection of data in WSN
Start
Setup phase
Selection of optimal cluster head
For each network N
$X_i^d = \{x_1^d, x_2^d, \dots., x_N^d\}$
$E_{B_i} = \{E_{B_1}, E_{B_2}, \dots \dots \dots, E_{B_N}\}$
    if node $N_i$ has normal data
        $E_{B_i} = 0$
        else
        $E_{B_i} = 1$
        Node has emergency data
    end
    if $D_{i,nei}(t) < d_0$
        $Nei_i = \{Nei_1, Nei_2, \dots., Nei_k\}$
        $E_i = \{E_1, E_2, \dots., E_k\}$
    end
    Compute the force by equation (1)
        If N is 2D, then
            $F^x{}_{i,j}(t) = G\frac{M_{pi}(t)*M_{aj}(t)}{D_{i,j}(t)}(X_j(t) - X_i(t))$          (2)
            $F^y{}_{i,j}(t) = G\frac{M_{pi}(t)*M_{aj}(t)}{D_{i,j}(t)}(Y_j(t) - Y_i(t))$          (3)
        End
        Compute weighted sum is by equation (4)
        Gravitational masses for the nodes are computed by equation (5)
        For j$\epsilon\{1,2,\ \ k\}$
            $best(t) = \max\{fit_j(t)\}$
            $worst(t) = \min\{fit_j(t)\}$
            Compute the fitness function of nearby emergency nodes by equation (9)
            Compute the fitness function of the Remaining energy of the node by equation (10)
                If $\alpha + \beta + \gamma = 1$
                 $fit_i = \alpha * fit_i^{emergency} + \beta * fit_i^{energy} + \gamma * (1 - fit_i^{cost})$
                 The acceleration as $acc_i^d = \frac{F_i^d(t)}{M_i(t)}$
                End for
        End
Steady Phase
    For $MA = \{MA_1, MA_2, \dots \dots . MA_{RMA}\}$
        Required number of MA calculated by equation (16)
        Allocating the source nodes to MA by equation (17)
        Compute the fitness function of data type by equation (18)
        Compute the fitness function of energy of the node by equation (19)
        If $\alpha + \beta + \gamma = 1$
            $fit_i = \alpha * fit_i^{data-type} + \beta * fit_i^{energy} + \gamma * fit_i^{distance}$
        End
    End for
End
```

5 Performance evaluation

5.1 Datasets

The public image datasets from targeted precision agriculture are presented in this section and are summarised in Table 2. Each dataset is described systematically and contains a range of details, such as the imaging device and setups, the quantity, format, and resolution of the images, the kind of annotation, the applications, and any potential restrictions. Only when the picture format – typically in png or jpg/jpeg – and resolution are constant throughout a given dataset are they described. These factors depend on the imaging instrument and post-processing techniques.

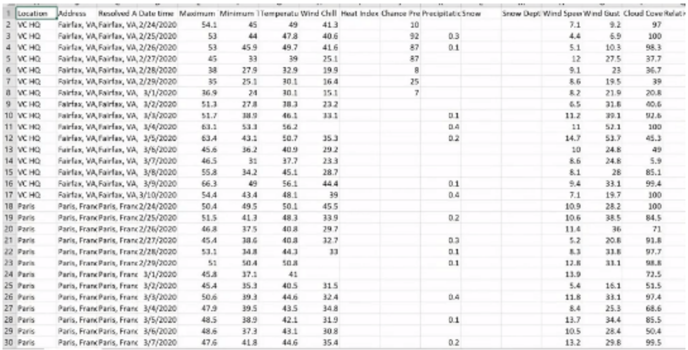
Table 2 Other precision agricultural applications have their public image collections (see online version for colours)

Dataset	*URL*
	https://www.kaggle.com/datasets/tanhim/agricultural-dataset-bangladesh–44-parameters
	https://braintoy.ai/2020/10/24/improve-farm-yield/

B	C	D	E	F
year	area	avg_rainfall	max_temperatur	min_temperatur
2008		2385	34.2	12.5
2008		2197	30.2	19.5
2008		2197	34.2	12.5
2008		2197	34.2	12.2
2008		1856	34.1	10.2
2008		2239	29.6	21.6
2008		2235	34.12	10.8
2009		1930	35.6	14.8
2009		1912	31	11.43
2009		1912	35.6	14.8
2009		1912	35.6	14.8
2009		1391	35.4	12.5
2009		1662	30.48	21.2
2009		1653	33	13.2
2010		1523	35.5	12.8
2010		1181	29.7	11
2010		1181	35	12.8
2010		1181	35	12.8
2010		1750	35	10.4
2010		2095	30.7	21.3
2010		1811	32.4	11.71

Record #	Sample #	Date_sampled	Time_elapsed_[days]	Site	Type	Hybrid	Wght[grams]	Amount	Size_category	Size_group	Cuml_Weight[kg_by_Hybrid	Cuml_Weight[kg]_by_Hybrid_and_size_category
1	1	13-May	61	1	1	1	0	0	1	1	0	0
33	2	15-May	63	1	1	1	0	0	1	1	0	0
65	2	15-May	63	1	1	1	0	0	1	1	0	0
97	2	18-May	66	1	1	1	0	0	1	1	0	0
129	2	21-May	69	1	1	1	360	1	1	1	0	0.36
161	2	23-May	71	1	1	1	0	0	1	1	1	0.36
193	2	25-May	73	1	1	1	0	0	1	1	1	0.36
225	3	27-May	75	1	1	1	0	0	1	1	2	0.36
257	4	29-May	77	1	1	1	0	0	1	1	3	0.36
289	5	2-Jun	81	1	1	1	0	0	1	1	5	0.36
321	6	5-Jun	84	1	1	1	410	1	1	1	10	0.77
353	7	10-Jun	89	1	1	1	2730	7	1	1	18	3.5
385	8	13-Jun	92	1	1	1	755	2	1	1	27	4.255
417	9	16-Jun	95	1	1	1	0	0	1	1	42	4.255
449	10	19-Jun	98	1	1	1	1115	3	1	1	60	5.37
481	10	23-Jun	102	1	1	1	810	2	1	1	77	6.18
513	11	26-Jun	105	1	1	1	0	0	1	1	88	6.18
545	12	29-Jun	108	1	1	1	0	0	1	1	97	6.18
577	13	2-Jul	111	1	1	1	0	0	1	1	102	6.18
609	14	6-Jul	115	1	1	1	0	0	1	1	105	6.18
641	14	10-Jul	119	1	1	1	0	0	1	1	108	6.18
673	15	13-Jul	122	1	1	1	0	0	1	1	109	6.18
705	16	17-Jul	126	1	1	1	0	0	1	1	109	6.18
737	17	21-Jul	130	1	1	1	0	0	1	1	110	6.18
769	18	24-Jul	133	1	1	1	0	0	1	1	117	6.18
801	19	28-Jul	137	1	1	1	0	0	1	1	125	6.18
833	20	31-Jul	140	1	1	1	0	0	1	1	135	6.18
865	21	4-Aug	144	1	1	1	425	1	1	1	144	6.585
897	22	7-Aug	147	1	1	1	0	0	1	1	149	6.585
929	1	6-Jun	61	2	1	1	0	0	1	1	0	0
961	2	12-Jun	67	2	1	1	0	0	1	1	1	0
[illegible]	3	20-Jun	75	2	1	1	2500	6	1	1	6	2.5

Table 2 Other precision agricultural applications have their public image collections (see online version for colours) (continued)

Dataset	*URL*
	https://www.visualcrossing.com/resources/category/documentation/weather-data-tutorials/page/2/

1	Location	Address	Resolved A	Date time	Maximum	Minimum	Temperatu	Wind Chill	Heat Index	Chance Pre	Precipitatic	Snow	Snow Dept	Wind Spee	Wind Gust	Cloud Cove	Relati
2	VC HQ	Fairfax, VA,	Fairfax, VA,	2/24/2020	54.1	45	49	41.3		10				7.1	9.2	97	
3	VC HQ	Fairfax, VA,	Fairfax, VA,	2/25/2020	53	44	47.8	40.6		92	0.3			4.4	6.9	100	
4	VC HQ	Fairfax, VA,	Fairfax, VA,	2/26/2020	53	45.9	49.7	41.6		87	0.1			5.1	10.3	98.3	
5	VC HQ	Fairfax, VA,	Fairfax, VA,	2/27/2020	45	33	39	25.1		87				12	27.5	37.7	
6	VC HQ	Fairfax, VA,	Fairfax, VA,	2/28/2020	38	27.9	32.9	19.9		8				9.1	23	36.7	
7	VC HQ	Fairfax, VA,	Fairfax, VA,	2/29/2020	35	25.1	30.1	16.4		25				8.6	19.5	39	
8	VC HQ	Fairfax, VA,	Fairfax, VA,	3/1/2020	36.9	24	30.1	15.1		7				8.2	21.9	20.8	
9	VC HQ	Fairfax, VA,	Fairfax, VA,	3/2/2020	51.3	27.8	38.3	23.2						6.5	31.8	40.6	
10	VC HQ	Fairfax, VA,	Fairfax, VA,	3/3/2020	51.7	38.9	46.1	33.1			0.1			11.2	39.1	92.6	
11	VC HQ	Fairfax, VA,	Fairfax, VA,	3/4/2020	63.1	53.3	56.2				0.4			11	52.1	100	
12	VC HQ	Fairfax, VA,	Fairfax, VA,	3/5/2020	63.4	43.1	50.7	35.3			0.2			14.7	53.7	45.3	
13	VC HQ	Fairfax, VA,	Fairfax, VA,	3/6/2020	45.6	36.2	40.9	29.2						10	24.8	49	
14	VC HQ	Fairfax, VA,	Fairfax, VA,	3/7/2020	46.5	31	37.7	23.3						8.6	24.8	5.9	
15	VC HQ	Fairfax, VA,	Fairfax, VA,	3/8/2020	55.8	34.2	45.1	28.7						8.1	28	85.1	
16	VC HQ	Fairfax, VA,	Fairfax, VA,	3/9/2020	66.3	49	56.1	44.4			0.1			9.4	33.1	99.4	
17	VC HQ	Fairfax, VA,	Fairfax, VA,	3/10/2020	54.4	43.4	48.1	39			0.4			7.1	19.7	100	
18	Paris	Paris, Franc	Paris, Franc	2/24/2020	50.4	49.5	50.1	45.5						10.9	28.2	100	
19	Paris	Paris, Franc	Paris, Franc	2/25/2020	51.5	41.3	48.3	33.9			0.2			10.6	38.5	84.5	
20	Paris	Paris, Franc	Paris, Franc	2/26/2020	46.8	37.5	40.8	29.7						11.4	36	71	
21	Paris	Paris, Franc	Paris, Franc	2/27/2020	45.4	38.6	40.8	32.7			0.3			5.2	20.8	91.8	
22	Paris	Paris, Franc	Paris, Franc	2/28/2020	53.1	34.8	44.3	33			0.1			8.3	31.8	97.7	
23	Paris	Paris, Franc	Paris, Franc	2/29/2020	51	50.4	50.8				0.1			12.8	31.1	98.8	
24	Paris	Paris, Franc	Paris, Franc	3/1/2020	45.8	37.1	41							13.9		72.5	
25	Paris	Paris, Franc	Paris, Franc	3/2/2020	45.4	35.3	40.5	31.5						5.4	16.1	51.5	
26	Paris	Paris, Franc	Paris, Franc	3/3/2020	50.6	39.3	44.6	32.4			0.4			11.8	33.1	97.4	
27	Paris	Paris, Franc	Paris, Franc	3/4/2020	47.9	39.5	43.5	34.8						8.4	25.3	68.6	
28	Paris	Paris, Franc	Paris, Franc	3/5/2020	48.5	38.9	42.1	31.9			0.1			13.7	34.4	85.5	
29	Paris	Paris, Franc	Paris, Franc	3/6/2020	48.6	37.3	43.1	30.8						10.5	28.4	50.4	
30	Paris	Paris, Franc	Paris, Franc	3/7/2020	47.6	41.8	44.6	35.4			0.2			13.2	29.8	99.5	

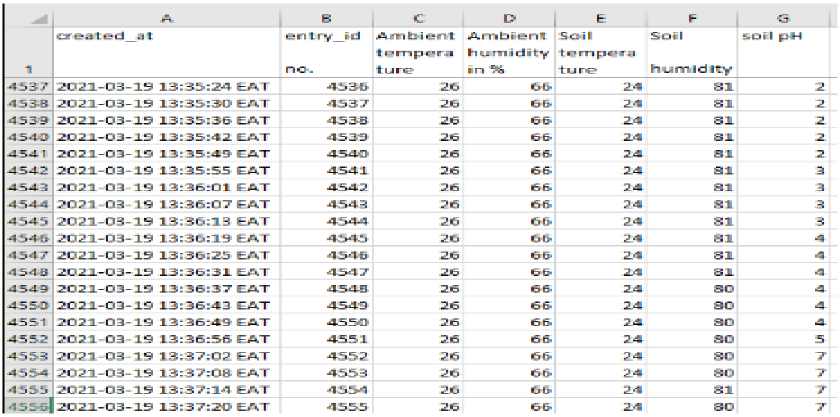
The proposed MF-GSA is put into practice in MATLAB. In 200×200 square unit space, 200 randomly distributed nodes made up a network. The BS was seen as being situated in the network's heart. Table 3 defines other simulation parameters utilised for the simulation. The effectiveness of the suggested clustering procedure was evaluated in terms of energy use and network longevity. The comparison was performed utilising the procedure provided to assess the MF-GSA efficiency.

Table 3 Simulation parameters set 1

Parameters	*Values*
Nodes	200
Deployment type	Random
Network area	200×200 square units
Size of packet	2000 bits
Initial energy	0.5 joules
E_{elec}	50 nj/bit
E_{fs}	10 pj/bit/m^2
Eda	5 nj/bit
Eamp	0.0013 pj/bit/m^4
Threshold distance	87.7 m

Table 4 (Mbandi, 2021) contains the data table defined for the data collection utilising WSN. The attached dataset contains recordings made for five parameters used to determine the physical composition of the soil. Between March 2021 and April 2021, data was gathered. The raw data is in this dataset. The dataset is in CSV format and contains 5 parameters for each ID in addition to the ID, date, and time the data was captured. This data table may be found at Redirect notice (2021).

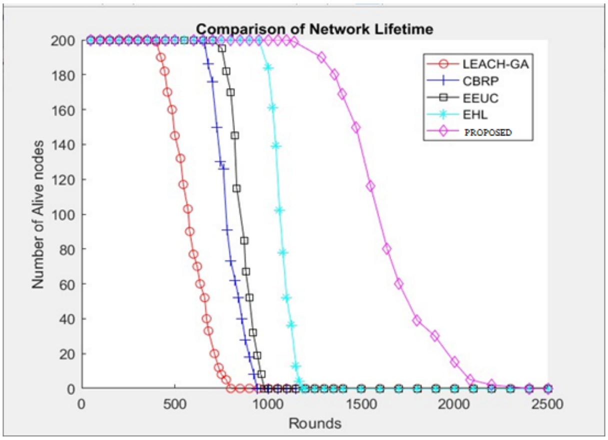
Table 4 The data table for data collection using WSN (see online version for colours)



	A	B	C	D	E	F	G
1	created_at	entry_id no.	Ambient temperature	Ambient humidity in %	Soil temperature	Soil humidity	soil pH
4537	2021-03-19 13:35:24 EAT	4536	26	66	24	81	2
4538	2021-03-19 13:35:30 EAT	4537	26	66	24	81	2
4539	2021-03-19 13:35:36 EAT	4538	26	66	24	81	2
4540	2021-03-19 13:35:42 EAT	4539	26	66	24	81	2
4541	2021-03-19 13:35:49 EAT	4540	26	66	24	81	2
4542	2021-03-19 13:35:55 EAT	4541	26	66	24	81	3
4543	2021-03-19 13:36:01 EAT	4542	26	66	24	81	3
4544	2021-03-19 13:36:07 EAT	4543	26	66	24	81	3
4545	2021-03-19 13:36:13 EAT	4544	26	66	24	81	3
4546	2021-03-19 13:36:19 EAT	4545	26	66	24	81	4
4547	2021-03-19 13:36:25 EAT	4546	26	66	24	81	4
4548	2021-03-19 13:36:31 EAT	4547	26	66	24	81	4
4549	2021-03-19 13:36:37 EAT	4548	26	66	24	80	4
4550	2021-03-19 13:36:43 EAT	4549	26	66	24	80	4
4551	2021-03-19 13:36:49 EAT	4550	26	66	24	80	4
4552	2021-03-19 13:36:56 EAT	4551	26	66	24	80	5
4553	2021-03-19 13:37:02 EAT	4552	26	66	24	80	7
4554	2021-03-19 13:37:08 EAT	4553	26	66	24	80	7
4555	2021-03-19 13:37:14 EAT	4554	26	66	24	81	7
4556	2021-03-19 13:37:20 EAT	4555	26	66	24	80	7

Figure 1 displays the variance in the number of live nodes to the number of rounds for the proposed along with existing algorithms. The number of active nodes is a good indicator of the network lifespan. Network lifespan is defined by the round at which the final node dies, whereas the round at which the first node dies determines the network stability period.

Figure 1 Comparison of network lifetime (see online version for colours)



The LEACH-GA clustering technique has the shortest network stability time (400 rounds), followed by CBRP and EEUC. While the suggested clustering algorithm has a stability network time of 1100 rounds, the EHL have the second-highest network stability time of 960 rounds. Additionally, a longer network lifespan enables us to deduce that the BS can receive more data. Both routine and urgent data are included in this. Consequently, we may deduce from the more favourable outcomes of the proposed data to the BS. Therefore, the proposed MFGSA algorithm promises higher performance for IoT applications using emergency data (Tables 5 and 6).

Table 5 Period of network stability for various algorithms

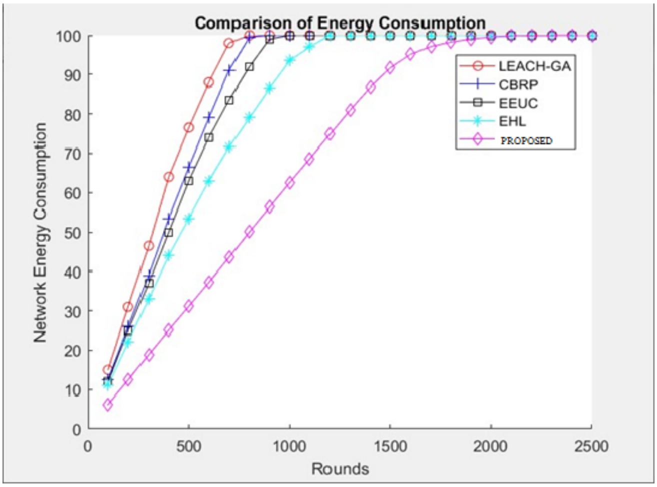
Algorithm	*Network stability period* (rounds)
LEACH-GA	400
CBRP	600
EEUC	720
EHL	960
Proposed MFGSA	1100

Table 6 The lifetime of various methods

Algorithm	*Network lifetime* (rounds)
LEACH-GA	780
CBRP	930
EEUC	970
EHL	1180
Proposed MFGSA	2240

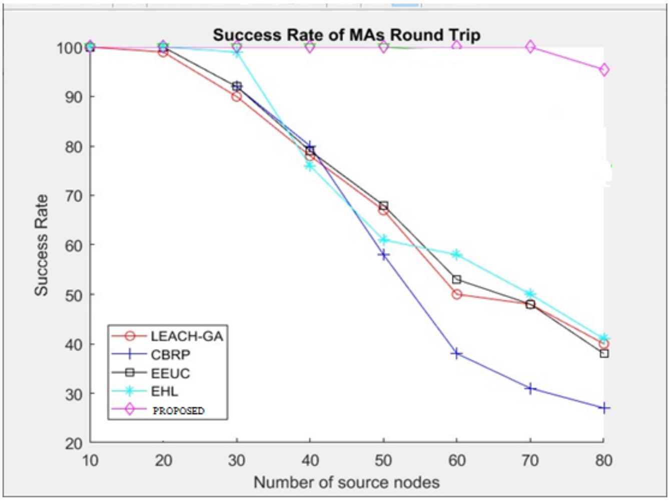
Figure 2 plots the network's energy use vs. the number of cycles. At first, 100 joules of energy were delivered to the network (0.5 Joules per node). When all the nodes have died out, the network's energy has been completely used. The energy was being used uniformly as the number of rounds rises. However, compared to previous algorithms that had sharp energy consumption rates, the suggested algorithm demonstrated a progressive increase in the rate of energy consumption. This is because multihop data transfer among CHby means of MA and more efficient cluster head selection using GSA.

Figure 2 Comparison of energy consumption (see online version for colours)



For this simulation, a larger network with 1000×500 square units was randomly distributed with 800 nodes. Between 10 and 80 source nodes were needed to broadcast data to the BS, and each node received 2 joules of energy. The success rate of MA trips with energy consumption was used to evaluate the network's performance. Figure 3 displays the fluctuation in the mobile agent's data-collecting trip's success rate.

Figure 3 Rate of mobile agent success (see online version for colours)



The success rate is calculated since the ratio of MAs dispatched through the BS toward MAs received by the BS intended for data collection. From the BS, MA is sent out to gather data from the source nodes. Failure is deemed to have occurred, whereas if BS does not always collect the MA. However, even when there were more source nodes, the suggested GSA-based strategy outperformed the others in terms of success rate. Consequently, the MA is allocated a selection of closely packed nodes, reducing the distance the MA must travel inside a cluster or group. The second part involves using GSA to optimise MA's route, which considers the nodes' remaining energy, the cost of their connections, and their available space starting from the BS to decide which nodes are most crucial for MA to visit. The primary concern for nodes containing ED is one of the higher priority nodes, which is visited first. The higher MA success rate of the suggested itinerary planning approach justifies it when compared to other tactics.

6 Conclusion

The sensor nodes that make up a WSN serve as the Internet of Things' skeleton. Increasing these nodes' lifespan would result in seamless support for IoT applications because smaller batteries power them. The cluster head selection procedure was optimised in this study utilising GSA. The nodes' remaining energy, the cost of their connections with the BS, and the number of nearby nodes who possessed emergency data were all factored in during the cluster head selection process. Furthermore, the final concept's ecotoxicity is not certain. All needs are considered concurrently when optimising retaining structures, and the final product is guaranteed to be optimised economically. Few researches have been carried out in recent years to create approaches again for the improvement of retaining walls. The MA was used to transmit the data, and the GSA was utilised once again to improve the MA's route. The simulation was run in

MATLAB to test the viability of employing GSA for the best cluster head choice. Energy usage and network lifetime were used to assess performance. Compared to other existing approaches, the suggested clustering methodology demonstrated superior performance. The task energy usage and MA trip success rate were used to assess the performance. The suggested method performed more successfully and used less energy when collecting data for MA.

References

Ajmi, N., Helali, A., Lorenz, P. and Mghaieth, R. (2021) 'MWCSGA-multi weight chicken swarm based genetic algorithm for energy efficient clustered wireless sensor network', *Sensors* (*Basel, Switzerland)*, Vol. 21, No. 3, p.791, doi: 10.3390/s21030791.

Amrani, A.E., Boukili, B., Hajjaji, A.E., Boumhidi, I. and Hmamed, A. (2021) 'H∞ model reduction design in finite frequency ranges for discrete-time Takagi-Sugeno fuzzy systems', *International Journal of System of Systems Engineering*, Vol. 11, No. 2, p.89, doi: 10.1504/ijsse.2021.116047.

Basha, R. and Yaashuwanth, A. (2019) 'Optimal partial collection based energy delay compromise technique for wireless sensor network', *IETE J. Res.*, Vol. 65, pp.855–871.

Bhushan, S., Kumar, M., Kumar, P., Stephan, T., Shankar, A. and Liu, P. (2021) 'FAJIT: a fuzzy-based data aggregation technique for energy efficiency in wireless sensor network', *Complex and Intelligent Systems*, Vol. 7, No. 2, pp.997–1007, doi: 10.1007/s40747-020-00258-w.

Borham, L., Khoriba, M. and Mostafa, G. (2021) 'Data collection protocols for wireless sensor networks', *Int. J. Electr. Comput. Eng. Syst.*, Vol. 12, pp.207–214.

Cao, L., Cai, Y. and Yue, Y. (2020) 'Data fusion algorithm for heterogeneous wireless sensor networks based on extreme learning machine optimised by particle swarm optimisation', *Journal of Sensors*, pp.1–17, doi: 10.1155/2020/2549324.

Dehkordi, S.A., Farajzadeh, K., Rezazadeh, J., Farahbakhsh, R., Sandrasegaran, K. and Dehkordi, M.A. (2020) 'A survey on data aggregation techniques in IoT sensor networks', *Wireless Networks*, Vol. 26, No. 2, pp.1243–1263, doi: 10.1007/s11276-019-02142-z.

Dewan, C., Kumar, T.G. and Gupta, S. (2022) 'A comparative analysis on remote user authentication schemes in telemedical healthcare systems', *International Journal of System of Systems Engineering*, Vol. 12, No. 2, p.134, doi: 10.1504/ijsse.2022.124980.

Faris, K., Asgarnezhad, R., Fathal, Z., Fleeh, A. and Mohammed, A. (2021) 'Survey of wireless sensor network based on power consumption and data aggregation', *International Journal of Progressive Research in Science and Engineering*, Vol. 2, No. 9, pp.22–32.

Ghaderi, M.R., Tabataba Vakili, V. and Sheikhan, M. (2020) 'FGAF-cDG: fuzzy geographic routing protocol based on compressive data gathering in wireless sensor networks', *Journal of Ambient Intelligence and Humanised Computing*, Vol. 11, No. 6, pp.2567–2589, doi: 10.1007/s12652-019-01314-1.

Grigoryan, G. and Collins, A.J. (2021) 'Game theory for systems engineering: a survey', *International Journal of System of Systems Engineering*, Vol. 11, No. 2, p.121, doi: 10.1504/ijsse.2021.116044.

Gupta, S., Gabrani, G. and Sharma, R. (2022) 'Student engagement and course motivation through experiential learning pedagogy', *International Journal of System of Systems Engineering*, Vol. 12, No. 1, p.1, doi: 10.1504/ijsse.2022.10046731.

Kalaikumar, K. and Baburaj, E. (2020) 'Fuzzy enabled congestion control by cross layer protocol utilising OABC in WSN: combining MAC, routing, non-similar clustering and efficient data delivery', *Wireless Networks*, Vol. 26, No. 2, pp.1085–1103, doi: 10.1007/s11276-018-1848-3.

Karunanithy, K. and Velusamy, B. (2020) 'Cluster-tree based energy efficient data gathering protocol for industrial automation using WSNs and IoT', *Journal of Industrial Information Integration*, Vol. 19, No. 100156, p.100156, doi: 10.1016/j. jii.2020.100156.

Liu, X., Qiu, T., Dai, B., Yang, L., Liu, A. and Wang, J. (2020) 'Swarm-intelligence-based rendezvous selection via edge computing for mobile sensor networks', *IEEE Internet of Things Journal*, Vol. 7, No. 10, pp.9471–9480, doi: 10.1109/jiot.2020.2973401.

Lyu, Z., Wei, Z., Wang, X., Fan, Y., Xia, C. and Shi, L. (2020) 'A periodic multinode charging and data collection scheme with optimal traveling path in WRSNs', *IEEE Systems Journal*, Vol. 14, No. 3, pp.3518–3529, doi: 10.1109/jsyst.2020.2977984.

Maivizhi, R. and Yogesh, P. (2021) 'Q-learning based routing for in-network aggregation in wireless sensor networks', *Wireless Networks*, Vol. 27, No. 4, pp.2231–2250, doi: 10.1007/s11276-021-02564-8.

Mbandi, J. (2021) *Soil Data Collection Using Wireless Sensor Networks* (*WSN) and Offsite Visualization: Case-Study of the Innovative Solutions for Digital Agriculture* (*iSDA*) *Project in Kenya*, IEEE DataPort.

Mohanty, S.N., Lydia, E.L., Elhoseny, M., Al Otaibi, M.M.G. and Shankar, K. (2020) 'Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks', *Physical Communication*, Vol. 40, No. 101097, p.101097, doi: 10.1016/j.phycom.2020.101097.

Osamy, W., El-Sawy, A.A. and Khedr, A.M. (2020) 'Effective TDMA scheduling for tree-based data collection using genetic algorithm in wireless sensor networks', *Peer-to-Peer Netw. Appl.*, Vol. 13, pp.796–815.

Osamy, W., Khedr, A.M., El-Sawy, A.A., Salim, A. and Vijayan, D. (2021a) 'IPDCA: intelligent proficient data collection approach for IoT-enabled wireless sensor networks in smart environments', *Electronics*, Vol. 10, No. 9, p.997, https://doi.org/10.3390/electronics10090997

Osamy, W., Salim, A., Khedr, A.M. and El-Sawy, A.A. (2021b) 'IDCT: intelligent data collection technique for IoT-enabled heterogeneous wireless sensor networks in smart environments', *IEEE Sensors Journal*, Vol. 21, No. 18, pp.21099–21112, doi: 10.1109/jsen.2021.3100339.

Raj, P.V.P., Khedr, A.M. and Aghbari, Z.A. (2020) 'Data gathering via mobile sink in WSNs using game theory and enhanced ant colony optimisation', *Wireless Networks*, Vol. 26, No. 4, pp.2983–2998, doi: 10.1007/s11276-020-02254-x.

Redirect notice (2021) *Google.com*, Available at. https://www.google.com/url?sa=i & url= https%3A%2F%2Fieee-dataport.org%2Fdocuments%2Fsoil-data-collection-using-wireless-sensor-networks-wsn-and-offsite-visualization-case&psig=AOvVaw3ZJ3cOtvqK9ow8ks_Kb T0t & ust=1663825014319000& source=images & cd=vfe & ved=2ahUKEwi5jOyolaX6A hVDcGwGHcJJDG8Qjhx6BAgAEAw (Accessed 8 December, 2022).

Sadeghi, F. and Avokh, A. (2020) 'Load-balanced data gathering in internet of things using an energy-aware cuckoo-search algorithm', *International Journal of Communication Systems*, Vol. 33, No. 9, p e4385, doi: 10.1002/dac.4385.

Sajedi, S.N., Maadani, M. and Nesari Moghadam, M. (2022) 'F-lEACH: a fuzzy-based data aggregation scheme for healthcare IoT systems', *The Journal of Supercomputing*, Vol. 78, No. 1, pp.1030–1047, doi: 10.1007/s11227-021-03890-6.

Sanjay Gandhi, G., Vikas, K., Ratnam, V., Suresh Babu, K., Gandhi, G.S., Vikas, K., Ratnam, V. and Babu, K.S. (2020) 'Grid clustering and fuzzy reinforcement-learning based energy-efficient data aggregation scheme for distributed WSN', *IET Communications*, Vol. 14, No. 16, pp.2840–2848, doi: 10.1049/iet-com.2019.1005.

Saranraj, G., Selvamani, K. and Malathi, P. (2022) 'A novel data aggregation using multi objective based male lion optimisation algorithm (DA-MOMLOA) 'in wireless sensor network', *Journal of Ambient Intelligence and Humanised Computing*, Vol. 13, No. 12, pp.5645–5653, doi: 10.1007/s12652-021-03230-9.

Sarode, P. and Reshmi, T.R. (2020) ‘Optimised query ordering data collection model using neural networks and group search optimization in wireless sensor network’, *Ad Hoc Sens. Wirel. Netw.*, Vol. 46, pp.189–214.

Sarode, P., Reshmi, T.R. and Pattabiraman, V. (2021) ‘Combination of fitness-mated lion algorithm with neural network for optimal query ordering data aggregation model in WSN’, *Wireless Personal Communications*, Vol. 116, No. 1, pp.513–538, doi: 10.1007/s11277-020-07726-z.

Seyfollahi, A. and Ghaffari, A. (2020) ‘Reliable data dissemination for the internet of things using Harris Hawks optimisation’, *Peer-to-Peer Netw. Appl.*, Vol. 13, pp.1886–1902.

Soundari, A.G. and Jyothi, V.L. (2020) ‘Energy efficient machine learning technique for smart data collection in wireless sensor networks’, *Circuits, Systems, and Signal Processing*, Vol. 39, No. 2, pp.1089–1122, doi: 10.1007/s00034-019-01181-3.

Pour, F.S.A. Tatar, U. and Tatar, A.V.G. (2022) ‘Blockchain empowered disaster recovery framework’, *International Journal of System of Systems Engineering*, Vol. 12, No. 1, pp.51–62.

Wei, X., Yan, S., Wang, X., Guizani, M. and Du, X. (2021) ‘STAC: a spatio-temporal approximate method in data collection applications’, *Pervasive and Mobile Computing*, Vol. 73, No. 101371, p.101371. Doi: 10.1016/j. pmcj.2021.101371.

Wijesinghe, S., Tolk, A., Handley, H., Barry, P. and Doskey, S. (2022) ‘Digital collaborators for complex systems development: a research agenda’, *International Journal of System of Systems Engineering*, Vol. 12, No. 1, p.1, doi: 10.1504/ijsse.2022.10042956.

Yun, W-K. and Yoo, S-J. (2021) ‘Q-learning-based data-aggregation-aware energy-efficient routing protocol for wireless sensor networks’, *IEEE Access: Practical Innovations, Open Solutions*, Vol. 9, pp.10737–10750, doi: 10.1109/access.2021.3051360.