Fuzzy based clustering and improved ant colony optimization for collecting data via mobile sink in wireless sensor networks

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Article Info	ABSTRACT
Article history: Received Nov 29, 2021 Revised Jul 4, 2023	Energy efficient routing of data from sensor to base station (BS) is attained utilizing the clustering of sensor nodes, thus minimizing the number of hops and circling the task of the cluster head (CH) sporadically. In addition, the clusters near to the BS take a substantial load over multi-hop communication.
Accepted Jul 8, 2023	The hot spot problem affects wireless sensor networks (WSNs) with BS nodes, which is caused by sensor nodes close to the BS allowing for increased
Keywords:	traffic load. So, the entire network lifespan is minimized owing to the element some nodes drain their energy resources much faster equated to the break. To solve these issues fuzzy based clustering and form the optimal route (FCOR) by mobile sink (MS) approach for efficient data collection is proposed. The fuzzy logic method is used for elected the CH by node remaining energy, node connectivity and node distance parameters. Discovering an optimal movable trajectory for the MS is serious so as to attain energy efficiency. Improved ant colony optimization (IACO) method is a better solution to discovering an optimal traversal route. Simulation results proves that FCOR increases the energy efficiency, throughput and minimized the network delay in the WSN.
Clustering Fuzzy logic system Improved ant colony Mobile sink Optimization method Sensor network	
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1. INTRODUCTION

wireless sensor networks (WSN) comprises a large quantity of sensor nodes disseminated over a definite area. The WSN acts a significant part in observation, commercialized,healthcare, and business mechanisation. Energy efficiency is an important tasks in developing WSNs. Enhancing energy-efficiency is a major concern since greater energy utilization confines the lifetime. Meanwhile data transmission has the the highest proportion of energy consumption, proficient routing is an operative resolution to such issue. Clustering is an operative method in making the WSN routing algorithms. Clustering is a dominant process broadly adjusted to raise the lifetime and minimize the communication energy utilization. Hierarchical clustering method is a mutual method to routing. In clustering, selecting the cluster head (CH) is a major concept and they essential to do additional tasks, thus they utilize additional energy. As a result, it is a significant issue to choose the optimal CHs.

In addition, the clusters near to the base station (BS) take a substantial load on multi-hop communication. Furthermore several traditional methods have not deliberated the redundant information gathering through the neighbor nodes. In WSN, sensor nodes near the BS allow additional traffic load. Therefore, the entire network lifespan is minimized. Nowadays, mobile sink (MS) is reflected as an excellentpolicy for solving the hot spot issue. MS actually move inside the WSN and collected the data and forward to the BS. The fuzzy method is used for elected the CH by node remaining energy, node connectivity

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and node distance parameters. Discovering an optimal movable trajectory for the MS is serious so as to attain energy efficiency. Improved ant colony optimization (IACO) method is a better solution to discovering an optimal traversal route. Take greatest percentage of energy use as follows. In section 2 explains the fuzzy based clustering and form the optimal route (FCOR) working function. Simulation analysis results are explained in section 3. Finally, it presents the conclusions in section 4.

Genetic algorithm and ant colony optimization (ACO) for the active cluster foundation by the node location and select the CH. This approach preserves additional energy. It enhances the network lifespan and throughput [1]. ACO based clustering method exactly with MS support for WSN. This approach the network is divide the many clusters and selected the CHs. Next, a MS transmission with every CH to gather information straightly via minimum range transmissions. The ACO technique applied for discovering the optimal route for the MS. This approach enhances the function of the network and improve the network lifespan [2]. ACO approach with MS is introduced for minimizing the amount of nodes straightly retrieved through destination and reduce the navigated route. This approach elects of rendezvous nodes by node density, residual energy, and the degree. Next, ACO is proposed to receive the optimal admittance route that can minimized delay and the utilization of energy [3]. Dynamic clustering with ACO-based MS approach to design an active clustering as well as optimal routing for collecting the data to enhance the lifespan. This approach is used for evading the hot spot problem. The ACO approach is adjusted for efficient route selection [4]. An improved ACO which applying MS based on CH distances. Here, the network is separated into many clusters also every cluster has one CH. The MS discovers an optimal method to transmit with CHs by ACO technique [5]. Compartmental model-based cluster size optimization applying opportunistic signals can be established on good signals availability. The compartmental model is used diminish the energy utilization and the clusters are formed by Taylor series expansion [6]. Improved energy-efficient the longevity is increased by using a clustering technique. The matching balanced clusters created by the fuzzy c-means to minimise and balance energy utilisation determine the ideal number of clusters. Then, using a back-off timer mechanism, CHs are selected at the best positions with CH replacement operation method for CH selection [7]. ARSH-FATI-based CH Selection method incorporated with a heuristic known ranked-based clustering for minimizing the energy transmission utilization when enhancing the lifespan. It deliberates the remaining energy, distance, and workload parameters are used for selecting the CHs [8].

Grey wolf optimizer (GWO) method is used in the fuzzy based enhanced CH selection (FBECS) strategy to choose the CHs. Grey wolves act as an intelligence algorithm known as GWO. It chooses the CHs based on how much energy each node uses and how much energy is still available. When the remaining nodes use single-hop transmission, this strategy balances energy consumption [9]. Although CH is easily dead, this method increases the overhead of CH routing. An effective and straightforward technique for time synchronisation is the time synchronisation approach [10]. The projection nodes are balanced using two compressive data collection methods. To evenly distribute the projection nodes and optimise energy usage, a spatial position-based clustering approach is also introduced. To evenly distribute the projection nodes and optimise energy usage, a spatial position-based clustering approach is also introduced. The lifespan of the network can be extended by even clustering by density, taking into account node position and density, and equal the network energy [11]. To meet the demands of cluster-based WSNs, single-channel cluster-based information-centric method, such as transmission between CH and child nodes [12].

Using a grid-based clustering technique, the load is first evaluated and then distributed. In order to achieve the nodes' energy utilisation at their level of energy, polynomials must be resolved to determine the ideal grid length. Finally, based on the ideal cluster size, the network is divided into uneven grids [13]. A creative optimisation with levy distribution through clustering technique employing a fitness function integrating four parameters, for example, energy, network load, distance to neighbours, and distance to the BS, is included in a hybridization of the metaheuristic cluster-based routing. For choosing the best course, a water wave optimisation with a hill-climbing method [14]. For achieving energy efficiency using the sleeping-waking method, an improved clustering hierarchy strategy is provided. With this method, data redundancy is decreased and network lifetime is increased [15]. Combining game to fight discriminating sending with clustering strengthens them by using unacceptable information from the non-cooperative game to boost forwarding rates. This clustering technique is required to transport packets in order to avoid detection [16]. The goal of the energy-efficient clustering technique is to maximise energy efficiency while minimising and equating energy usage. To reduce energy overhead, the lemma relating to the dual-CH approach is applied. The goal of a noncooperative game method is to balance how much energy each CH uses. Energy efficiency is improved by the energy-efficient clustering algorithm mutual game theory with dual-CH technique. It extends the network lifespan [17]. The CH is chosen using an improved artificial bee colony algorithm based on node density, node energy, and node position. The fuzzy c-means clustering method was used to construct the grouping. After that, create an ACO routing algorithm between the CH and BS that is energy-efficient. The network throughput is improved by this method [18]. To measure and improve dependability, one uses the end-to-end data delivery reliability strategy. This method delays the mapping operation between the received signal strength (RSS), background noise, and packet reception ratio. However, this strategy falls short in terms of energy efficiency and network longevity [19].

Using CS and ACO methods to construct an energy-efficient routing. Here, the ACO method is utilised to find the leader nodes, and the CS method is applied to choose the data forwarder node during data transmission. However, this method's inefficiency with regard to energy during multiple hops [20]. A clustertree routing approach using self-organizing entropy for selecting the CH. compressive sensing technique is used to aggregate and compressed the data. Through CHs and the BS, the routing tree is applied to compressed data. The next step is to use a bee-based signal reconstruction algorithm to speed up the recovery process and find the best optimality and improves the lifetime [21]. A neighbor discovery method and two greedy k-hop clustering approach concentrate on bi-channel connectivity when enhancing the lifetime. Nodes remaining energy, awareness of spectrum, channel quality, and the distance between nodes parameters for choosing the hop count and channels for clusters. It enhances the network lifetime and network stability [22]. Provisioning of efficient authentication approach using elliptic curve cryptography (ECC) method to improve the authentication [23]. Diffie Hellman and the black-box information method on possibilistic queries and sporadic verification is to minimize the costs [24]. Signed digit number system applying neural network to contract with the mathematics functions that service the use of neural networks [25]. The entire traditional approach described the sensor node's localization. However, they demand a large amount of computation power, and this power grows as computational complexity increases [26]. Link quality is expressed through link quality evaluation. Although unstable [27], this strategy. The localization methods are typically divided into two categories, such as the distance using angle of arrival, residual signal strength indication (RSSI), and time of arrival [28]. To improve the quality, link quality is measured using RSSI. It does, however, increase computing complexity [29].

2. FUZZY BASED CLUSTERING AND IACO FOR COLLECTING DATA VIA MS IN WSN 2.1. Network formation

Network formation is expected here each sensor node has equal abilities regarding sensing region, transmission power. In this approach, every node has the same energy. Node RSSI is applied for compute the distance between nodes. We form the clusters by node distance. Figure 1 demonstrates the structure of the FCOR approach. After form the network, the sensor nodes are disseminating the hello message that consist of sensor ID inside its transmission range. From these hello message the number of neighbours with every node measured their distance.



Figure 1. Architecture of FCOR approach

2.2. Fuzzy based CH selection

In this approach, the fuzzy method is used for selecting the CH by the sensor node remaining energy, node connectivity and distance from sensor node to BS. Sensor node remaining energy is a significant factor for choosing a CH meanwhile a CH node has to utilize additional energy than a sensor node. A CH node gathers data from sensor and communicates these data to the data collector. One-hop neighbouring nodes inside the transmission node is known as node connectivity. This factor that decides how a node is positioned in the middle among its neighbours. The energy utilization for forwarding data raises with expand in distance between sender and BS nodes. From an energy management viewpoint, the distance between CH and BS could be reduced. The maximum energy, minimum distance and highest node connectivity node is elected as a CH based on fuzzy method. Figure 2 explains a fuzzy logic system of FCOR approach.



Figure 2. Fuzzy logic system of FCOR approach

Little, average, and greater are the remaining energy of fuzzy set variables. Near, medium and long distance for the distance of fuzzy variable set. In addition, near, accessible, and unfriendly for node connectivity fuzzy set input variables. The chance of CH selection output variables is very small, small, slightly small, small average, average, great medium, slightly great, great, and very great. The data collector node is selected by the highest node energy. Thus, minimized the node dead problem in the network.

2.3. MS form the route by ACO

ACO is now inspired by the ant's behaviour in its natural environment. It demonstrates the moral adequate function by using graphs to find the best routes. The fundamental characteristics of the ACO technique are uncertainty, flexibility, and distribution. It is a form of positive feedback system. It is suitable for exact solution and parallel calculation.

Here, we treat the MS as a salesman, the data collector is plays as a city and the MS will visit all data collectors. The MS will travel the most efficient path used by the ACO method to reach data collector locations and collect data using one hop actually close communications. The communication distance between MS and the data collector is relatively tiny, which significantly reduces the energy consumption of the data collector. The ACO approach employs a heuristic element to increase the qualities on the following node, to enhance the convergence rate and to expand the capability of global search. Consequently, the latency is reduced. However, drawbacks of ACO method are functional inefficiency due to the ant's diversity, which it is simple to decrease into local convergence and received the route typically cannot meet with the solution of a possible solution, ants choose the next data collector to be travelled via a policy of probabilistic decision. While ant k visits in data collector m also builds the partial solution, at time t, the possibility movable to the next data collector n neighboring data collector m is computed as:

$$P_{mn}^{k}(t) = \frac{\gamma_{mn}^{\lambda}(t)\beta_{mn}^{\omega}(t)}{\sum_{k \in allowed_{k}} \gamma_{mn}^{\lambda}(t)\beta_{mn}^{\omega}(t)} \quad f \ n \in allowed_{k}$$
(1)

here $\gamma_{mn}^{\lambda}(t)$ represents the pheromone trail at time on arc (m,n) at time t, $\beta_{mn} = \frac{1}{d_{mn}}$ represents the heuristic value of movable from data collector m to n, *allowed*_k denotes the set of ant k visited data collector. λ as well as ω indicate the factors which control the comparative pheromone trail weight and heuristic value.

Though the ACO method has several shortcomings for example, convergence slow rate and it is simple to decrease into local optimal solution. Thus, we introduce the IACO method to improve the global search capacity and enhance the convergence rate. We raise the effect of the MS node to the next data collector, and enhance β_{mn} by applying the lesser distance between the data collector to the MS node, accordingly:

$$\beta_{mn} = \frac{1}{\min[dist_{mn} + dist_{n,o}]} \tag{2}$$

here, dist (m, n) represents the distance from data collector m to next data collector node n and dist (n, o) represents the distance from data collector o to the MS node m. Applying (2) into (1):

$$P_{mn}^{k}(t) = \begin{cases} \frac{\gamma_{mn}^{\lambda}(t) \cdot \left\{\frac{1}{\min[dist_{mn}+dist_{n,0}]}\right\}}{\sum_{k \in allowed_{k}} \gamma_{mn}^{\lambda}(t) \cdot \left\{\frac{1}{\min[dist_{mn}+dist_{n,0}]}\right\}} & \text{if } n \in allowed_{k} \end{cases}$$
(3)

the pheromone trail on a route disperses over time. After time, the trail concentration is updated by:

$$\gamma_{mn}(t+s) = \varsigma \gamma_{mn}(t) + \Delta \gamma_{mn}(t) \tag{4}$$

$$\Delta \gamma_{mn}(t) = \sum_{k=1}^{r} \gamma_{mn}(t) \tag{5}$$

Here, ς represents the coefficient that denotes the disappearance of trail between time *t* and *t*+*s* and its value between 0 and 1. $\Delta \gamma_{mn}(t)$ denotes the per unit of length of trail substance quantity represents the ant's count. This procedure will end until an optimal route is establishing afterward a given number of iterations. Finally, the MS collected the data from the data collector and forward the data to BS in the WSN.

3. RESULTS AND DISCUSSION

The simulations are applied to equate FBECS and FCOR approaches. Network simulator-2.35 is utilized for measuring the quality of service (QoS) parameters. The network scenario in which the sensor nodes are present randomly. Here, constant bit rate traffic is used for data transmission.

3.1. Packet forward ratio

Figure 3 explains the packet forward ratio of FBECS and FCOR based on number of nodes. It shows the number of packets forward efficiently to the BS. The ratio of packets forwarded is greater in the FCOR mechanism compared to the FBECS mechanism. Because of, the MS collect the data from data collector node efficiently by ACO algorithm. As a result, it increases the packet forward ratio. But the existing mechanism minimized the packet forward ratio.



Figure 3. Packet forward ratio of FBECS and FCOR based on number of nodes

3.2. Packet drop ratio

Figure 4 demonstrates the packet drop ratio of FBECS and FCOR based on number of nodes. In the FCOR mechanism, the packet drop ratio is lesser than the FCOR mechanism using the fuzzy method is select

the efficient CH based on node energy and node distance from BS. Although, FBECS mechanism have the highest packet drops in the WSN since it increasing the energy utilization.



Figure 4. Packet drop ratio of FBECS and FCOR based on number of nodes

3.3. Lifetime

Figure 5 demonstrates the comparison of CH lifetime for FBECS and FCOR by number of nodes. As number of sensor node raises, the CH lifetime also raised. This shows that the required QoS is not the absolute owing breaking of the route since if it were, nodes would relocate. However, the FCOR method CH's current lifetime is between 700 and 650 seconds. However, the FBECS approach lifespan is between 425 and 500 seconds.



Figure 5. CH lifetime of FBECS and FCOR based on number of nodes

3.4. Remaining energy

Figure 6 specify the remaining energy of FBECS and FCOR by number of nodes. The FCOR mechanism is increases the remaining energy compared to the existing FBECS mechanism. The FCOR approach minimized the CH dead by the data collector. In addition, the MS minimized the CH energy utilization in the WSN. But, FBECS mechanism can't use the MS thus increases the CH energy consumption in the network.

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Figure 6. Remaining energy of CS, MACO, and CSHC approaches for node density

4. CONCLUSION

In this strategy, an energy efficient improved ant colony optimisation based approach is demonstrated for WSN with MS. Node RSSI is utilized for computing the sensor nodes distance. We select the CHs by fuzzy logic method based on node remaining energy, node connectivity and node distance. The data collector node is selected by the highest node energy. Thus, minimized the node dead problem in the network. The MS gathers data through an optimal moving route that is decided through IACO method, then collects the BS is received the data from the data collector. Finally, the MS forward the data to BS. As a result, the data is received in a timely manner. The simulation outcomes demonstrate that the FCOR approach executes mainly well equated to other method thus it improves the WSN lifetime. In addition, it increased both the energy efficiency and throughput also it minimized the network delay.

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