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A routing approach based on combination of gray wolf clustering and fuzzy clustering and using multi-criteria decision making approaches for WSN-IoT

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ABSTRACT

The Internet of Things (IoT) plays a crucial role across diverse sectors such as industrial, educational, and healthcare. Ensuring stable and efficient network performance is essential for these applications, making optimal routing a critical factor. Proper clustering of network nodes is pivotal, as it enhances network efficiency and prolongs its lifetime by reducing energy consumption. This study proposes a novel routing approach for IoT networks based on Wireless Sensor Networks (WSN), called GWFCCV (Gray Wolf and Fuzzy Clustering and using Critic and Fuzzy Vikor approaches). Our method employs a combination of Gray Wolf Optimizer (GWO) and Fuzzy C-Means (FCM) for clustering, alongside multi-criteria decision-making techniques to rank and select nodes for efficient routing. Simulation results demonstrate that GWFCCV significantly improves key network parameters, including energy consumption, throughput, and network lifetime, outperforming existing approaches such as EACMRP-MS, FEEC-IIR, and FRLDG. For example, it can increase the lifetime of the network by 5.43 %, 8.3 % and 23.26 %, respectively.

1. Introduction

Considering its importance, the Internet of Things (IoT) can have a great impact on the world economy, and based on the predictions made in the coming years, it will cause increasing economic growth in the world. Accordingly, telecommunication companies

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have a very important duty towards this technology to minimize the challenges in the path of this technology. According to the estimates, it has been estimated that the number of objects that are equipped with the Internet is more than the number of people on the planet, which means that this technology will receive more traffic from the Internet in the future [1]. The capabilities of this technology, including the smartening of cities and homes, have caused the growing trend of this technology to increase in the future, and devices equipped with the Internet will also have an upward trend. This makes it possible to consider solutions to solve the challenges associated with this technology because this technology is based on a centralized system architecture, which has caused limitations of the devices used in this technology, such as low computing power and limited storage capacity [2]. With all the limitations mentioned, the benefits of this technology can create a huge transformation in the world of information technology so that it can connect heterogeneous devices in different environments and in different sizes through the Internet to exchange information [3]. A very important feature in IoT technology is the connection of heterogeneous devices, it is even possible to consider the possibility of accurate tracking of locations. High security and privacy can also be considered, especially in wireless communication [4]. Routing is a critical issue in the Internet of Things, as effective routing enhances the reliability and security of information transmitted across the network. This is particularly significant in sectors such as healthcare, where timely and accurate data delivery is essential for both patients and healthcare providers. Consequently, having an optimal routing path is fundamental in IoT [5]. Various algorithms are used for routing in IoT, resulting in improvements in network longevity, lower latency, higher packet delivery rates, increased reliability, and other key performance metrics. These improvements underline the importance of proper routing in maintaining the quality of IoT networks [6]. In this context, the AODV (Ad hoc On-demand Distance Vector) protocol plays a vital role in routing within Wireless Sensor Networks (WSN) and IoT. AODV's key advantage is its ability to establish routes only when necessary, optimizing energy consumption and minimizing control message overhead. This makes it especially suitable for networks with dynamic topologies and resource-constrained devices, such as IoT nodes. AODV enhances network scalability by supporting large-scale deployments while ensuring loop-free and efficient routing. It also reduces latency by quickly creating routes and performing local repairs when a route breaks, improving network fault tolerance. With its support for multi-hop communication, low-bandwidth adaptation, and compatibility with IoT protocols like CoAP and MQTT, AODV offers an optimal solution for reliable and efficient routing in WSN-IoT networks. In our daily activities, various systems rely on the Internet of Things, including computer systems, mobile phones, and home appliances. These devices enable us to perform tasks seamlessly through interconnected networks. Additionally, vehicular ad hoc networks integrate IoT with vehicles, facilitating routing, data collection, and intelligent functionalities. Communication between IoT devices occurs wirelessly, highlighting the critical need for robust security and privacy measures to safeguard data transfer effectively [7]. With the increasing security threats, ensuring the existence of a safe path for information exchange through a secure routing strategy has become one of the important challenges in the Internet of Things. Existing routing protocols face many problems and challenges to create reliability. One of these challenges is usually using devices in the Internet of Things with low battery life, limited processing capability, and limited memory. Also, the presence of dynamic topology in the Internet of Things increases security risks due to the nature of mobile sensors and nodes and the permission given to nodes to connect to or leave the network without predefined information. Consequently, these factors impose detrimental consequences on security protocols. While robust cryptographic algorithms exist, implementing them in the constrained IoT environment remains problematic due to their high computational requirements and resource demands and this is a great motivation for having an optimal routing [8]. In uncertain environments or when faced with ambiguities, fuzzy logic enables decision-making by incorporating concepts of probability and ambiguity. This approach proves valuable in assessing and evaluating features with inherent uncertainty, such as node performance in IoT networks. Using the fuzzy system and applying multi-criteria decision making methods makes it possible to effectively evaluate the Internet of Things systems based on various criteria such as reliability, communication delay and energy consumption. These methods facilitate node prioritization based on multiple attributes, thus enhancing overall network performance [9]. In this research, by using an optimal clustering and also by using multi-criteria decision making techniques along with fuzzy system, an optimal route has been found in the WSN based Internet of Things. Among the contributions of this research, the following can be mentioned:

- We propose a novel hybrid algorithm called GWFCCV, which combines Fuzzy C-Means (FCM) and the Grey Wolf Optimizer (GWO) to enhance clustering in wireless sensor networks. This integration improves both clustering accuracy and stability.
- The GWO algorithm optimizes the initial cluster centers obtained from FCM, refining them to reduce intra-cluster distances and enhance the overall quality of clustering.
- We employ a dynamic weighting scheme to select cluster heads based on multiple criteria, including residual energy, throughput, and node memory, utilizing the CRITIC method.
- To improve routing efficiency, we apply the Fuzzy VIKOR method to rank nodes based on residual energy, throughput, and available memory, ensuring optimal routing decisions and efficient packet delivery.

In the continuation of this research, these sections will be mentioned. In Section 2, previous related works are mentioned. Section 3 describes the methods used in the proposed idea. In Section 4, the proposed approach is presented. In Section 5, the evaluation of the proposed approach is presented, and finally, in Section 6, the conclusion of the research is presented.

2. Related work

In this section, some of the previous researches regarding clustering and route finding in the Internet of Things and sensor networks will be discussed. In [10], an energy-aware routing strategy for IoT-based wireless sensor networks is presented, which results in increased network lifetime. The basis of this approach is based on two phases, determining appropriate clustering and routing in the network. The simulation of this approach in MATLAB software has shown good results in criteria such as residual energy, network lifetime, and packet delivery ratio. In [11], an approach to increase the lifespan of the Internet of Things network according to the gray wolf optimization algorithm based on the sunflower algorithm is proposed. This approach starts a multi-path routing by the sunflower algorithm, which selects the optimal path by integrating the gray wolf algorithm and the sun flower optimization algorithm. The results and evaluations of this research show improvement in network throughput, network delay, network lifetime and maximum energy consumption. In [12], a new approach to prevent attacks in dynamic Internet of Things network is developed. This approach is based on reliable routing. The mentioned approach is a combination of meta-heuristic algorithms, and specifically, sunflower flower optimization algorithm and atom search optimization (ASSFO) are used. In this routing, reliable nodes are selected by the reliability coefficient, which has shown favorable results regarding energy consumption, maximum reliability and throughput. In [13], a multi-objective optimization approach for routing in the Internet of Things is developed. This approach is based on two stages, in the first stage, a trust model is presented to select the cluster head, and in the second stage, a hybrid algorithm based on particle swarm optimization and genetic algorithm is used for data transfer. The results of this approach show improvement in the residual energy of nodes, throughput, and improvement in packet delivery ratio and increase in energy efficiency. In [14], a clustering-based approach is proposed to improve routing in IoT wireless sensor networks. In this approach, a genetic optimization algorithm is used for network clustering and cluster head selection, as well as a balance optimization algorithm for routing between cluster heads. The results and evaluations of this research in MATLAB software compared to the other approaches show the improvement of network lifetime, packet delivery ratio and also the use of energy. In [15], a routing strategy for IoT wireless sensor networks is proposed. This approach is developed to present a multipath routing protocol using particle swarm optimization algorithm that can be used for networks with high load volume. Simulation results with NS-2 software have been compared with approaches such as AODV and DSDV, which have yielded favorable results in saving energy, reducing end-to-end delay, increasing packet delivery ratio, and increasing throughput. In [16], a multi-hub and energy-aware routing protocol for the Internet of Things is developed. The purpose of providing this protocol is to try to reduce the use of energy and thus increase the lifetime of the network. This protocol selects the optimal cluster head and operates based on fuzzy logic. The evaluation results of this approach show the improvement of the performance of this approach during the lifetime of the network, the delivery rate of packets, the improvement of the delay in the network and as a result, the increase of the network efficiency. In [17], a routing algorithm is proposed in the wireless Internet of Things network, which improves energy consumption with optimal routing. In this approach, the objective function criteria for clustering include error rate, low energy consumption, Euclidean distance and packet delivery ratio. This approach has used the WSA optimization algorithm for clustering and selecting cluster heads. Ant colony optimization algorithm has been used for routing between cluster heads. The simulation results show an improvement in the survival rate of the nodes, an improvement in the packet delivery ratio, and a more optimal energy consumption compared to the other algorithms. In [18], a trust-based routing approach called TBIEERP is proposed for the Internet of Things home network. In this approach, a SHA-Secure Hashing algorithm is used to encrypt and decrypt data. The results of this approach show the improvement of attack detection through appropriate routing in the Internet of Things. In [19], a bio-algorithm-inspired routing protocol called TSA is introduced for IoT-based wireless sensor network. This algorithm is used to find the optimal cluster head based on parameters such as distance and energy. This algorithm has been compared with other meta-heuristic methods that have shown favorable results in increasing the lifetime of the network. Table 1 summarizes related works done regarding routing in the Internet of Things.

Table 1
A summary of previous related work.

Ref.	Routing approach	Achievements & weaknesses
[10]	An approach for improved energy in IoT-Based WSN	Improving PDR, end-to-end delay, low energy consumption, no concern for reliability
[11]	An approach to increase the lifetime of IoT network	Improving delay, maximum energy consumption, network lifetime, throughput, no concern for reliability
[12]	An approach to prevent attacks in dynamic IoT network	Improving energy consumption, maximum reliability, throughput, not paying attention to delay
[13]	A multi-objective optimization approach for routing in IoT	Improving remaining energy, throughput, PDR, energy efficiency, not paying attention to the delay
[14]	An approach for clustering and routing in WSN based on IoT	Improving network lifetime, PDR, energy consumption, lack of attention to delay
[15]	A routing approach for IoT-based wireless sensor networks	Improving energy, reducing E-to-E delay, increasing PDR, throughput, lack of attention to reliability
[16]	An energy aware IoT routing protocol for increase network lifespan	Improvement in PDR, low energy consumption and end-to-end delay reduction, ignore security
[17]	An approach in wireless IoT to reduce energy consumption	Improving the node aliveness rate, PDR, optimal energy consumption, not paying attention to delay
[18]	A trust-based routing approach for IoT home network	Improving the detection of attacks due to proper routing, not paying attention to the delay and PDR
[19]	A routing protocol called TSA for IoT-based WSN	Increasing network lifetime, PDR not paying attention to reliability
Proposed	A routing approach for IoT-based WSN called GWFCCV	Increasing throughput, network lifetime and PDR. Reducing energy consumption, end-to-end delay and packet lose

3. Material and methods

In this section, an explanation about the gray wolf algorithm, the fuzzy clustering algorithm, as well as the used fuzzy multi-criteria decision-making approaches and the AODV route discovery protocol will be given and examined.

3.1. Gray wolf optimization algorithm

One of the relatively new algorithms among meta-heuristic algorithms is the gray wolf optimization algorithm, which was discovered in 2014 by Mir Jalili and his colleagues. Compared to other meta-heuristic algorithms, this algorithm has high exploration and exploitation power, and its high convergence speed has made it suitable for linear optimization problems perform well. The basis of its operation is based on the attack of gray wolves to hunt, which is done in four layers. The first to third layers consist of alpha, beta and delta wolves, which act as leader wolves and help the omega wolves (fourth layer) to hunt. The method of hunting is summarized in three steps: 1-encirclement, 2-prey and 3-attack [20]. Eqs. (1) and (2) show the stages of trapping prey:

$$\vec{D} = \left| \vec{C}\vec{X}_p(t) - \vec{X}(t) \right| \tag{1}$$

$$Y = \vec{X}_p(t) - \vec{A} \times \vec{D} \tag{2}$$

In Eqs. (1) and (2), t is the number of iterations of the algorithm, $\vec{X}_p(t)$ is the prey position in the number of iterations of the algorithm, $\vec{X}(t)$ is the current position of the gray wolf in the iteration of the algorithm, and Y is the updated position of the gray wolf at the location $\vec{X}(t)$. The vectors $\vec{A}$ and $\vec{C}$ are also the coefficients of the prey location vector which is obtained from Eqs. (3) and (4).

$$C = 2 * r1 \tag{3}$$

$$A = 2 * a * r2 - a \tag{4}$$

The value of a in Eq. (4) is calculated from Eq. (5).

$$a = 2 - \frac{2 * t}{Max\ iteration} \tag{5}$$

In Eqs. (3) and (4), $r1$ and $r2$ are two random values in the range of 0 and 1([0,1]).a is a coefficient that represents the acceleration of movement, its value decreases from 2 to 0 during the iteration steps of the gray wolf optimization algorithm. To model the hunting attack, it can be assumed that the top three wolves, namely Alpha, Beta, and Delta, can lead an Omega wolf, so the attack modeling by these top three wolves is shown in Eqs. (6)–(8) [20].

$$Y1 = \alpha - A1 \times |C1 * \alpha - x(t)| \tag{6}$$

$$Y2 = \beta - A2 \times |C2 * \beta - x(t)| \tag{7}$$

$$Y3 = \delta - A3 \times |C3 * \delta - x(t)| \tag{8}$$

In Eqs. (6)–(8) the attack modeling by alpha, beta and delta wolves is shown, respectively. In the above equations,$C1$, $C2$ and $C3$ are three random numbers in the range of 0 to 2 [0,2] . $A1$, $A2$ and $A3$ are also parameters for effective exploration and exploitation. To update the position of the Omega Wolf based on the modeling provided by the top three wolves, the position of the Omega Wolf can be updated from the Eq. (9).

$$Y(t+1) = \frac{Y1 + Y2 + Y3}{3} \tag{9}$$

3.2. FCM algorithm

The purpose of creating a fuzzy clustering algorithm is to use it at the time of uncertainty, and this uncertainty can be represented by the membership function that indicates the degree of membership of a sample to a cluster [21]. In fact, a fuzzy matrix can be used for the probability of a point belonging to a cluster, which shows the membership degree of that point. Fuzzy clustering has faster convergence speed than hard clustering like K-Means and shows better local search than hard algorithms. The degree of membership in this clustering algorithm can be the Euclidean distance or the similarity of the point to other points around it [22]. Eq. (10) shows the Fuzzy C-means clustering algorithm equation.

$$Min\ J_m(U, V) = \sum_{i=1}^{n} \sum_{j=1}^{c} \left(\mu_{ij}\right)^m D(x_i, v_j) \tag{10}$$

In Eq. (10), $\mu_{ij}$is the membership matrix of each point to a cluster and V is a set of cluster centers, which, naturally, the value of v_j represents the center of cluster$j$. m indicates the number of overlapping clusters and $D(x_i,v_j)$ is the Euclidean distance of a point x_i to the center of cluster v_j. Algorithm 1 shows clustering by FCM algorithm. In the FCM algorithm used in the proposed method, the number of clusters (c) was determined based on an initial analysis of the data and the objective of clustering, with the optimal result achieved with $c = 4$. The fuzzy factor was set to 2 ($m = 2$), which provides a suitable balance between the memberships. The convergence threshold (λ=0.01) was selected to ensure high accuracy in convergence. The value TMAX=50 was set as the maximum number of iterations to limit the algorithm's execution time and prevent infinite loops, as the algorithm usually converges within these 50 iterations. Table 2 shows the characters used for the FCM algorithm (Algorithm 1).

3.3. Critic approach

One visual method for determining the weight of selected criteria in multi-criteria decision-making approaches is the Critic method. This method operates based on the conflict and interaction of factors and criteria in decision-making, with minimal reliance on expert opinions in weight determination. This approach uses the standard deviation of criteria values in each column and the correlation coefficients between columns [23]. The steps of the Critic method are shown below:

Step 1: In the first step, a decision-making matrix is created, based on which criteria and alternatives are determined.

Step 2: In the next step, the decision matrix created in the previous step is normalized by using Eq. (11).

$$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \tag{11}$$

Step 3: In this step, the standard deviation of each alternative and its correlation with other criteria are considered, which is shown in Eq. (12).

$$w_j = \frac{C_j}{\sum_{k=1}^{m} C_i} \tag{12}$$

In Eq. (12), w_j is the weight of criterion*j*, C_i is the amount of information of the sum of k criteria, which is from 1 to *m*, and C_j is the information extracted from criterion *j*, which is obtained from Eq. (13).

$$C_j = \sigma_j \sum_{k=1}^{m} (1 - r_{kj}) \tag{13}$$

In Eq. (13), σ_j is the standard deviation of the *j*th criterion and r_{kj} is the correlation between two criteria *j* and*k*. The higher the value of C_j, the greater the weight of that criterion.

3.4. Fuzzy VIKOR approach

One of the key approaches for ranking alternatives in multi-criteria decision-making is the VIKOR method. This approach enables a comprehensive evaluation of the performance of alternatives. When considering uncertain and subjective judgments, it can be applied within a fuzzy environment [24]. Proposed by Opricovic and Tzeng in 2002, the VIKOR method offers a compromise solution close to the ideal and ranks the alternatives in the order of being close to the ideal solution [25]. Algorithm 2 presents the Fuzzy VIKOR approach, while Table 3 lists the variables used in the Fuzzy VIKOR algorithm. Also, Table 3 shows the characters used for the Fuzzy VIKOR algorithm and Table 4 provides a ranking example for four sample nodes, A, B, C, and D, based on the Fuzzy VIKOR output. In this table, S_j^* is the best value of the criterion for node j, indicating the ideal performance for that criterion. S_j^- represents the worst value of the criterion for node j, indicating the least favorable performance. S_l is the utility value for node*l*, reflecting the overall utility of the node considering all criteria. F_l is the regret value for node *l*, representing the potential regret for selecting that node. Finally, Q_l is VIKOR index for node *l*, which is a composite index that ranks the node by balancing utility and regret. "Rank" column shows the final ranking of the nodes based on the VIKOR index Q_l, where the node with the lowest $Q_l$is ranked first (in this example, node B is ranked first).

Table 2
The characters used for the FCM algorithm.

Symbol	Description
c	Number of clusters
y	Data points or input vectors
m	Fuzziness parameter (controls the degree of fuzziness in clustering)
Λ	Convergence threshold for stopping the algorithm
	Iteration index (each iteration of the algorithm)
	Maximum number of allowed iterations
X	Set of data points, consisting of $x_1, x_2, \ldots, x_n$
U^t	Membership matrix at iteration t, containing membership degrees μ_{ij}
μ_{ij}	Membership degree of data point i to cluster j
v_j	Centroid of cluster j
$abs\left(\mu_{ij}^t - \mu_{ij}^{t+1}\right)$	Absolute difference between membership degrees in iterations t and $t+1$

Algorithm 1
Fuzzy C-Means algorithm.

FCM Algorithm

```
1   Begin
2   Determine the value for c, y and m;
3   Determine the value for threshold "λ" for convergence;
4   Initial t: = 0,    TMAX: = 50;
5   X: = {x_1 .... x_n};
6   U^(t) := {μ_11 ... μ_ij} randomly generated
7   Calculate centroids:
8   Calculate the centroid v_j
9   Classification:
10  Calculate and update the membership matrix U^(t+1) := {μ_ij}
11  Convergence
12    If max [abs (μ_ij^(t) − μ_ij^(t+1)] < "λ" or t ≤ TMAX):
13      Stop the algorithm;
14   Otherwise;
15   U^(t) := U^(t+1) y t: = t + 1;
16  Go to Line 9
17  End
```

Algorithm 2
Fuzzy VIKOR approach algorithm.

Fuzzy VIKOR Algorithm
1*Buildafuzzydecisionmatrix*;
2*Determiningtheweightofcriteria*;
3 *Normalizing the fuzzy decision matrix by*: $\widetilde{S}^{TN_{ij}} = \frac{\widetilde{S}^{T_{ij}}}{\sum_{i=1}^{m} \widetilde{S}^{T_{ij}2}}$;
4 *Determining the best* S_j^* *and* S_j^- *by* : $S_j^* = \max_j \widetilde{S}^{TN_{ij}}$ && $S_j^- = \min_j \widetilde{S}^{TN_{ij}}$;
5 *Calculating utility*(S)*and regret* (F)*by* : $\widetilde{S}_l = \sum_{j=1}^{n} \frac{\widetilde{w}_j \left(S_j^* - \widetilde{S}^{TN_{ij}}\right)}{\left(S_j^* - S_j^-\right)}$ && $\widetilde{F}_l = \max_j \left[\frac{\widetilde{w}_j \left(S_j^* - \widetilde{S}^{TN_{ij}}\right)}{\left(S_j^* - S_j^-\right)}\right]$;
6 *Computing VIKOR index Q by* : $\widetilde{Q}_l = \vartheta \frac{(\widetilde{S}_i - S^-)}{(S^* - S^-)} + (1 + \vartheta) \frac{\widetilde{F}_i - F^*}{F^* - F^-}$ *where* $0 < \vartheta < 1$;
7*SortallalternativesbasedonQ*;

Table 3
The characters used for the Fuzzy VIKOR algorithm.

Symbol	Description
$\widetilde{S}_{ij}^{T}$	Fuzzy decision matrix element for alternative *i* and criterion *j*
w_j	Weight of criterion *j*
$\widetilde{S}_j^*$	Ideal (best) value for criterion *j*
$\widetilde{S}_j^-$	Anti-ideal (worst) value for criterion *j*
S_l	Utility function value for alternative *l*
$\widetilde{F}_l$	Regret function value for alternative *l*
$\widetilde{Q}_l$	VIKOR index for alternative *l*
ϑ	Weighting parameter for the compromise solution (where $0<\vartheta<10$)
S_j^*	Maximum normalized value of criterion j (ideal)
S_j^-	Minimum normalized value of criterion j (anti-ideal)
F_j^*	Maximum normalized regret value (ideal)
F_j^-	Minimum normalized regret value (anti-ideal)

Table 4
Ranking example derived from the Fuzzy VIKOR algorithm output.

Node	S_j^* (Best)	S_j^- (Worst)	S_l (Utility)	F_l (Regret)	Q_l(Vikor index)	Rank
A	0.85	0.60	0.72	0.78	0.80	2
B	0.90	0.55	0.88	0.75	0.70	1
C	0.70	0.50	0.65	0.68	0.85	4
D	0.75	0.55	0.70	0.72	0.83	3

3.5. AODV routing protocol

The AODV routing protocol, which is a reactive protocol, supports both unicast and multicast communications and is used to establish routes to the destination. This protocol has two main components: route discovery and route maintenance, which are crucial for finding the shortest path between the sender and receiver [26]. Figs. 1 and 2 show these two phases. Each node in the network maintains a table for storing route information and neighbors, including statistics such as destination, hop count, and node lifespan. When data needs to be sent, the node first checks the available routes, and if no route is found, the route discovery process is initiated. AODV uses four types of control messages, including Route Request (RREQ), Route Reply (RREP), Route Error (RERR), and Hello messages to manage the route discovery and maintenance process. RREQ message is used to discover a route from a source node to a destination node. When a source node needs to find a route to a destination, it broadcasts an RREQ message throughout the network. The RREQ message contains information such as the source node's address, the destination node's address, and a unique request ID to help identify and differentiate between different route requests. Once the RREQ message reaches the destination node or an intermediate node with a valid route to the destination, a RREP message is sent back to the source node. The RREP message provides the source node with the route information needed to reach the destination, including the sequence number and the path metrics. Hello messages are used for neighbor discovery. In the AODV algorithm, the RERR message indicates that a problem or failure has occurred in the route from the source to the destination. This message is triggered when a node realizes that it can no longer use an existing route, usually due to the failure of an intermediate node or a broken link between nodes. The RERR message is sent to inform all nodes using that route that it is no longer valid, prompting them to initiate a new route discovery process. This dynamic mechanism allows the network to quickly respond to changes or failures, ensuring that data flow continues by finding alternate paths. The AODV protocol is well-suited for Wireless Sensor Networks based on IoT (WSN-IoT) due to its reactive nature and its ability to find optimal routes with low overhead. This protocol is particularly useful in dynamic and resource-constrained environments like WSN-IoT, where it offers high efficiency in managing energy and bandwidth. Additionally, AODV's ability to quickly respond to changes in network topology makes it ideal for such networks. In Fig. 1, the Route Discovery phase of the AODV algorithm is illustrated. As shown in the Fig. 1, the source node S sends Route Request (RREQ) messages to all its neighbors W, P, and V. The RREQ packets are sent from all routes to the neighboring nodes and they check in their routing table whether there is a route or not. If the route is not found, this repetition of sending the RREQ packet will continue. After reaching the final destination D, the destination node creates the RREP message packet and then sends it to the source through the shortest path.

In Fig. 2, which depicts the Route Maintenance phase, it is shown that if a route established between the source node S and destination node D via nodes W and U becomes unusable due to receiving an RERR message, an alternative route will be provided through nodes P and M or through nodes V and C [26].

4. Proposed method

The aim of this study is to find a suitable and optimal route to transfer packets on wireless sensor network base Internet of things. To do this, a hybrid algorithm called GWFCCV has been proposed. The proposed approach combines Fuzzy C-Means (FCM) and Grey Wolf Optimizer (GWO) for efficient network clustering. Initially, FCM performs clustering by assigning data refer to clusters with different degrees of membership. These cluster centers are then refined using GWO, which iteratively optimizes the positions based on a fitness function that maximizes cluster quality. Cluster heads are selected using a dynamic weighting scheme that considers residual energy,

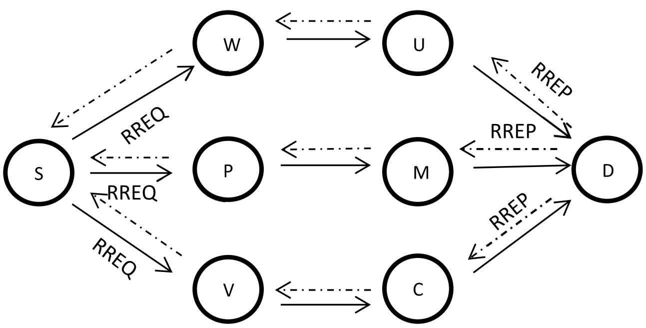

Fig. 1. Route discovery phase.

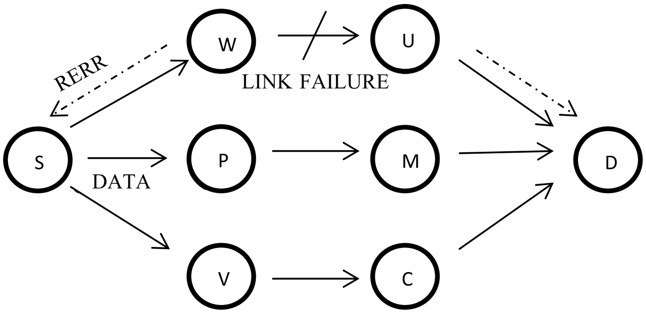

Fig. 2. Route maintenance phase.

throughput, and node memory. For routing, the weights of the criteria are determined using the CRITIC method, including residual energy, throughput, and distance between nodes. The Fuzzy VIKOR method is then applied, ranking nodes based on criteria such as residual energy, throughput and free memory, ensuring optimal routing decisions. This hybrid approach improves clustering accuracy, stability, and routing efficiency in network environments. The steps of proposed approach are as follow:

4.1. Clustering the networks

At first, the network is clustered by Fuzzy C-Means algorithm, the steps of this approach will be explained below.

Step1: In the first step, the FCM algorithm is initiated by defining the number of clusters C and randomly initializing the membership matrix, where each element u_{ij} represents the degree of membership of data point x_i in cluster, ensuring that the sum of memberships for each data point equals to 1.

Step2: In the second step, the cluster centers C_j are updated based on the membership matrix, which is shown in the Eq. (14).

$$C_j = \frac{\sum_{i=1}^{n} u_{ij}^{m} \cdot x_i}{\sum_{i=1}^{n} u_{ij}^{m}} \tag{14}$$

In Eq. (14), m is the fuzziness parameter and u_{ij} is the membership of data point x_i in cluster.

Step3: In this step, the membership values u_{ij} are updated for each data point and each cluster by using the Eq. (15).

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{|x_i - C_j|}{|x_i - C_k|} \right)^{\frac{2}{m-1}}} \tag{15}$$

In Eq. (15), $|x_i - C_j|$ is the distance based on the Euclidean distance between the data point x_i and the cluster center C_j.

Step4: In this part, the FCM algorithm iteratively repeats the processes of updating the cluster centers and membership values until the change in the membership matrix U between successive iterations falls below a predefined threshold, indicating that the algorithm has converged. We considered the threshold limit in this paper to be 0.01 %, which means that the iterations will stop when the change in the membership matrix U between consecutive iterations is very small relative to the number of data points.

4.2. Optimization of cluster centers using GWO

In this part, after clustering the network, the cluster center optimize by GWO algorithm. To do this, Initialize the positions of grey wolves (solutions) corresponding to the cluster centers obtained from FCM. After that, a fitness function is used to evaluate the quality of the clustering solution. In this new approach, according to Eq. (16), F is used as a fitness function to maximize the number of clusters while minimizing noise and enhancing cluster compactness and separation.

$$F = n_c * (1 - noise_{ratio}) * \ cluster_{density} * \ silhouette_{avg} * \ \frac{1}{intra - cluster\ variance} \tag{16}$$

In Eq. (16), n_c is a number of cluster, $noise_{ratio}$ is a proportion of data points classified as noise. $cluster_{density}$is the average density of clusters, indicating how closely packed the data points are within clusters and calculate by Eq. (17). $silhouette_{avg}$Is the average silhouette score, using Eq. (18), the similarity of an object to its own cluster is calculated compared to other clusters. $intra - clustervariance$ is the average variance within clusters, with lower values indicating more compact clusters which calculate by Eq. (19).

$$cluster_{density} = \frac{1}{n_{cluster}} \sum_{i=1}^{n_{cluster}} \left(\frac{|C_i|}{\sum_{p \in C_i} d(p, \mu_i)} \right), \quad \mu_i = \frac{1}{|C_i|} \sum_{p \in C_i} p \tag{17}$$

$$silhouette_{avg} = \frac{1}{n} \sum_{p \in D} \frac{b(p) - a(p)}{\max(a(p),\ b(p))} \tag{18}$$

$$ICV = \frac{1}{c} \sum_{j=1}^{c} \frac{1}{n_j} \sum_{i=1}^{n_j} ||x_i - C_j||^2 \tag{19}$$

In Eq. (18), n is a number of points, $b(p)$ and $a(p)$ is the minimum average distance of p with other points of the other cluster and the average distance of p with other points in the same cluster, respectively.

In Eq. (19), C in a number of clusters, n_j represents the number of data points that are in cluster j, x_i is the i th data point in cluster j, C_j is the center of cluster j and $||x_i - C_j||$ is the Euclidean distance between data and the cluster center.

In next level, the initial positions of the wolves are set to the cluster centers obtained from the FCM algorithm. In this case, X represent the positions of the wolves, which are X_α, X_β, X_δ and other wolves. The Control Parametersα, A, and C are defined. The parameter α decreases linearly from 2 to 0 over the course of iterations which show in Eq. (20).

$$\alpha = 2 - 2 * \frac{t}{T} \tag{20}$$

In Eq. (20), t and T are the current iteration and the maximum iteration number, respectively. The parameters A and C are calculated by Eqs. (21) and (22):

$$A = 2\alpha\ .\ r_1 - \alpha \tag{21}$$

$$C = 2.r_2 \tag{22}$$

Where r_1 and r_2 are random vectors range from 0 to 1.

This initialization ensures that the grey wolves have starting positions based on the FCM cluster centers and control parameters that guide their movement towards optimal cluster centers.

After these steps, the positions of the grey wolves are updated iteratively according to the positions of the three best wolves, β*and*δ as Eq. (23), Eqs. (24) and (25):

$$D_\alpha = |C_1.\ X_\alpha - X| \tag{23}$$

$$D_\beta = |C_2.\ X_\beta - X| \tag{24}$$

$$D_\delta = |C_3.\ X_\delta - X| \tag{25}$$

In these equations, D is a distance vectors and C are coefficient vectors that calculated by using Eq. (26). In Eq. (26), $r_i$are random vectors range from 0 to 1.

$$C_i = 2\ .\ r_i \tag{26}$$

After that, calculate the updated positions X_1,X_2andX_3 will be done by Eq. (27)–(29).

$$X_1 = |X_\alpha - A_1\ .\ D_\alpha \tag{27}$$

$$X_2 = |X_\beta - A_2\ .\ D_\beta \tag{28}$$

$$X_3 = |X_\delta - A_3\ .\ D_\delta \tag{29}$$

Where, A_1, $A_2$and $A_3$are coefficient vectors calculated using Eq. (30).

$$A_i = 2\alpha\ .\ r_i - \alpha \tag{30}$$

Finally, the update position of the grey wolf calculates by Eq. (31).

$$X = \frac{X_1 +\ X_2 +\ X_3}{3} \tag{31}$$

These equations iteratively adjust the positions of the grey wolves, guiding them towards the optimal cluster centers by mimicking the hunting behavior of grey wolves. This process continues until the stopping criterion is occurs. After that, the fitness of the new positions is evaluated using the fitness function in Eq. (16) and the update process is repeated until the maximum number of iterations is reached or the positions converge.

4.3. Cluster head selection

Node weights are calculated based on three criteria: node memory, residual energy, and throughput. Each node is evaluated using these criteria, and the weights are determined by combining these criteria.

$$W_i = w_i * Memory_i + w_e * Residul\ energy_i + w_t * Throughput_i \tag{32}$$

In Eq. (32), w_i, $w_e$andw_t are the weights assigned to memory, residual energy, and throughput, respectively. These weights are calculated using the CRITIC method. The CRITIC method calculates the weights of each criteria by Standardize the Decision Matrix, which each criterion value X_{ij} is standardized to remove the effects of different scales.

$$Z_{ij} = \frac{X_{ij} - \overline{X_j}}{\sigma_j} \tag{33}$$

In Eq. (33), X_{ij} is the value of criterion j for node i, $\overline{X_j}$ is the mean of criterion j across all nodes, σ_j is the standard deviation of criterion j across all nodes and Z_{ij} is the standardized value. After that, the Contrast Intensity (C_j) for each criterion is calculating by Eq. (34).

$$C_j = \sqrt{\sum_{i=1}^{n} \left(Z_{ij} + \overline{Z_j}\right)^2} \tag{34}$$

Where, $\overline{Z_j}$ is the mean of the standardized values of criterion j and n is the number of nodes. The Correlation Coefficient r_{jk} between criteria is calculating by Eq. (35):

$$r_{jk} = \frac{\sum_{i=1}^{n} \left(Z_{ij} - \overline{Z_j}\right)\left(Z_{ik} - \overline{Z_k}\right)}{(n-1)\sigma_{Zj}\sigma_{Zk}} \tag{35}$$

Where, σ_{Zj} is the standard deviation of the standardized values of criterion j and σ_{Zk} is the standard deviation of the standardized values of criterion k. The Information Content (IC_j) is calculating by Eq. (36):

$$IC_j = C_j\left(\sum_{k=1, k\neq j}^{m} (1 - r_{jk}\right)) \tag{36}$$

Where, m is the total number of criteria and the weight W_j is calculated according to the information content of each criteria. The node with the highest combined weight (W_j) in each cluster is selected as the cluster head.

$$W_j = \frac{IC_j}{\sum_{j=1}^{m} IC_j} \tag{37}$$

4.4. Calculation of distance of a node and residual energy of nodes

As mentioned, two factors are considered for choosing the right cluster, first the distance from the center of the cluster obtained by the Eq. (38) (Euclidean distance), and second the residual energy of each node, which is calculated from the Eq. (39).

$$D = |X - Y| = \sqrt{\sum_{i=1}^{n} (X_i - Y_i)^2} \tag{38}$$

$$RE = \frac{E_w - EC_w}{E_w} \tag{39}$$

In Eq. (39), E_w represents the total energy in node w and EC_w represents the energy consumed by node w. To obtain the energy consumption of a node, the energy of the node must be calculated in its different states, which is calculated from Eq. (40).

$$EC_w = V \times \left[\alpha T + \beta T + \gamma T + \delta T + \sum_t pT\right] \tag{40}$$

In Eq. (40), T is the desired time for the different modes that the node has, α is the low consumption mode of the node, β shows the mode of data transmission by the node, γ represents the mode in which the node receives the data, δ is the flow state of the hardware for the node to be active, p is the current required by the sensors connected to the node and V is the required voltage of the node.

Table 5
Criteria used to rank nodes during routing.

Name of criteria	Symbols
Residual energy	C1
Throughput	C2
Free memory	*C3*

4.5. Calculation of routing criteria

For the ranking of nodes, it is necessary to consider criteria so that optimal nodes can be selected for routing and packets transmission. The calculation of the optimal node will be done by the Fuzzy VIKOR approach along the way. Table 5 shows the ranking criteria of the nodes.

4.5.1. Residual energy of the node

One of the influential and important factors in routing is the residual energy or the amount of energy available in the node, which is necessary to continue the activity in the network, and its value is calculated by Eq. (39).

4.5.2. Node memory

Node memory means the amount of space that a node has the capacity to store packet in it. The more memory a node has, the more packets it can store and send. The amount of this memory is calculated from the routing table information for each node.

4.5.3. Throughput

The throughput of a node is the amount of packets that pass through the corresponding node and are delivered to the destination in a given time. By specifying this value, the ability of each node to send passing packet is determined, which shows the importance of that node. The amount of throughput of each node is calculated from Eq. (41).

$$Throughput = \frac{H_i}{T} \tag{41}$$

In Eq. (41), H_i is the symbol of packets that pass through node i without problems and loss, and T is a certain time interval.

4.6. Calculation of weight, decision matrix and linguistic variables

As mentioned before, we use the Critic method to calculate the weights of the nodes in the fuzzy VIKOR approach as well as the weights of the criteria. One of the advantages of using the Critic method is that no additional data is needed to calculate the weight of each criteria, and the weight of the criteria is calculated with the same fuzzy decision matrix that is used for the fuzzy VIKOR approach. The fuzzy VIKOR decision matrix for ranking 4 nodes is shown in, Table 6, although the weight of each criteria is also calculated based on the same decision matrix and with the Critic method.

The linguistic variables constituting the decision-making matrix in Table 6 are specified by Table 7, which are equivalent to the linguistic variables used in the decision-making matrix.

After forming the matrix by linguistic variable, the fuzzy VIKOR approach will be used to rank the nodes by these three criteria in routing, and the steps of which can be seen in the Algorithm.2. The linguistic variables in Table 7 are designed to represent a range of performance levels for the nodes. The decimal values (e.g., (0, 0.05, 0.15) for "Very Weak") are chosen to provide high sensitivity and precision in evaluating node performance. This approach allows for detailed differentiation between performance levels, which is crucial for accurate fuzzy logic analysis. Table 6 is populated using the linguistic variables from Table 7. For example, the values in Table 6 for remaining energy e.g., (0.5, 0.65, 0.8) correspond to the performance levels defined in Table 7. The use of decimal values reflects the high sensitivity required in the decision-making process. If less precision were needed, integer values might be used, but decimal values ensure a more nuanced and precise assessment of node performance.

5. Performance evaluation

To simulate the proposed algorithm, we utilized the Cooja simulator environment, which is based on the Contiki operating system and is highly suitable for Internet of Things (IoT) simulations. In our evaluations, we compared the results of the proposed GWFCCV method with the FRLDG [7], EACMRP-MS [16], and FEEC-IIR [27] methods. In the FRLDG (Fuzzy-based Routing with Low-energy and Dynamic Grouping) method, an energy-aware fuzzy logic-based routing approach for IoT is presented. This method utilizes the Harris Hawk Optimization (HHO) for optimization purposes. In the EACMRP-MS (Energy Aware Clustering and Multihop Routing Protocol with Mobile Sink) method, an approach for energy-aware clustering control and a multi-hop routing protocol for WSN-IoT are provided. This method relies on the Tunicate Swarm Algorithm (TSA) for cluster head selection and cluster formation. Additionally, fuzzy logic techniques are employed to optimally select multi-hop routes. In the FEEC-IIR (Fuzzy-based Energy-Efficient Clustering with Intelligent and Integrated Routing) method, an optimization approach in routing for WSN-IoT is proposed using the Water Strider

Table 6
Fuzzy decision matrix.

Criteria Alternative	Residual energy(C1)	Throughput(C2)	Free memory(C3)
Node **1**	(0.5, 0.65, 0.8)	(0.2, 0.35, 0.5)	(0, 0.05, 0.15)
Node **2**	(0.7, 0.65, 0.8)	(0.3, 0.5, 0.7)	(0.1, 0.2, 0.3)
Node **3**	(0.2, 0.35, 0.5)	(0.85, 0.95, 1)	(0.3, 0.5, 0.7)
Node **4**	(0.5, 0.65, 0.8)	(0.2, 0.35, 0.5)	(0.7, 0.8, 0.9)

Table 7
Linguistic variables and corresponding triangular fuzzy numbers.

Importance of linguistic variables	Equivalent to linguistic variables
Very weak	(0, 0.05, 0.15)
Weak	(0.1, 0.2, 0.3)
Relatively weak	(0.2, 0.35, 0.5)
Medium	(0.3, 0.5, 0.7)
Relatively good	(0.5, 0.65, 0.8)
Good	(0.7, 0.8, 0.9)
Very good	(0.85, 0.95, 1)

Algorithm (WSA) and Ant Colony Optimization (ACO).

The simulation parameters used in these evaluations are summarized in Table 8.

To mitigate the potential impact of randomness in the simulation results, we repeated each simulation five times and calculated the average of the outcomes. This randomness arises from certain parameters or events being determined randomly or through random numbers in a computer simulation. Consequently, this can lead to variations in the simulation results across different runs, affecting metrics such as packet loss rate and end-to-end delay. In our approach, key parameters for the Grey Wolf Optimizer (GWO) include the population size m and the number of iterations t, while for the Fuzzy C-Means (FCM) algorithm, the number of clusters k and the fuzziness coefficient m_f are crucial. These parameters were initially selected based on previous research and subsequently fine-tuned through empirical testing to achieve a balance between convergence speed and clustering accuracy. Specifically, we conducted sensitivity analyses to assess how different parameter values impact performance metrics such as intra-cluster distance and network lifetime.

For the proposed method, the GWO parameters were set to $m = 18$ and $t = 50$. Additionally, the FCM parameters were selected as $k = 5$ and $m_f = 2$. The selection of these parameters was informed by empirical testing and optimization efforts. The number of clusters and the fuzziness coefficient in FCM were chosen to balance clustering quality with computational efficiency. For GWO, the population size and iterations were selected to ensure effective exploration and convergence. Overall, these parameter choices contribute to maintaining a low time complexity, demonstrating efficient performance even in large-scale networks.

5.1. Energy consumption

Energy consumption is the amount of energy that a node uses during its activity in the network. The total energy consumption of all nodes in a network is considered as the total energy consumption of that network. Fig. 3 shows the comparison of energy consumption of different methods. According to the Fig. 3, it is proved that the energy consumption in the proposed GWFCCV approach for different number of nodes is lower than the FEEC-IIR and FRLDG approaches. Only when the number of nodes is 200, the proposed method has a poorer performance than EACMRP-MS, but it has performed better than this method in other cases. Of course, due to the random nature of the simulations, this weakness can be overcome by repeating the simulations. By reducing the energy consumption, it is possible to save the remaining energy of the nodes and as a result increase the life of the network in the Internet of Things.

5.2. Throughput

Throughput indicates the power of network nodes to transmit packets safely and without losing packets in a certain period of time, which can increase the quality of network performance in packet transmission. Fig. 4 shows the comparison of various methods in terms of throughput. As shown in Fig. 6, the proposed method has more improvement than other methods in terms of throughput. This indicates that the packets passing through the nodes in the network with respect to a certain time are more than other approaches and it can perform better even in the large-scale network with more nodes.

Table 8
Simulation parameters.

Parameters	Values
Number of nodes	**450**
Node's Speed	**60 m/s**
Initial energy of node	**2 *j***
Packet size	**1000 bits**
Frequency	**2.4GHz**
Bandwidth	**20 MHz**
Number of iterations	**100**
Simulation time	**2500 *s***
Environment size	**100×100 m**
Communication range	**35 m**

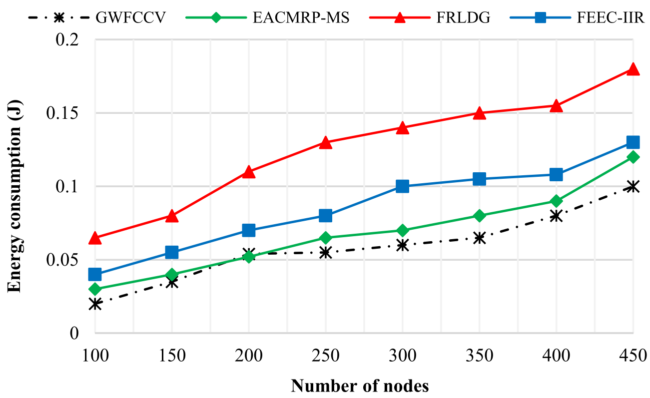

Fig. 3. Comparison of energy consumption in different methods.

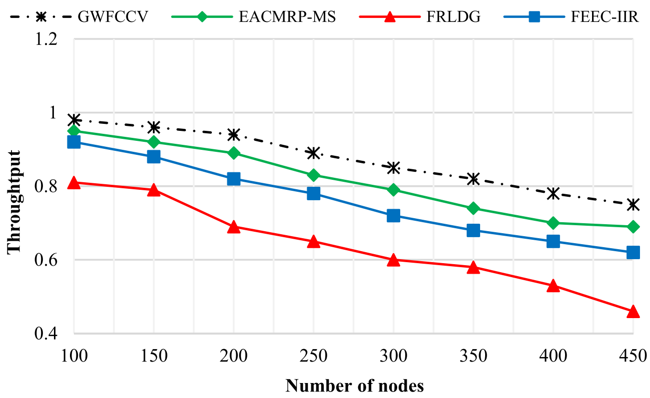

Fig. 4. Comparison of throughput of different methods.

5.3. packet delivery ratio

The good result of the throughput of the proposed approach showed that the improvement of the throughput has a positive effect on the improvement of the package delivery ratio, so that the proposed method can improve and increase the number of healthy packages delivered to the destination compared to other methods. Fig. 5 shows the comparison of packet delivery ratio in the proposed method and other methods.

5.4. End-to-end delay rate

The time it takes for a packet to be sent from the source node to the time it is received at the destination node is called end-to-end delay. Fig. 6 shows the end-to-end delay of the proposed method compared to other methods. By paying attention to Fig 6, it is clear that the proposed method (GWFCCV) has better performance in terms of end-to-end delay compared to the FRLDG and FEEC-IIR methods in all cases. Only when the number of nodes is 100, the EACMRP-MS method has less delay than the proposed method, but in other cases the proposed method has proven its superiority.

5.5. Packet loss rate

Losing packets and not reaching their destination safely can significantly reduce the quality and capabilities of the network, so it can be considered an important factor to have a stable network. In Fig. 7, the packet loss rate is examined according to the number of nodes.

As shown in Fig. 7, the proposed method has a lower packet loss rate than other methods. Only in the case that the number of nodes is <180, it has shown a weaker performance than the EACMRP-MS approach. As mentioned earlier, this state can be affected by the randomness of the simulation and its conditions, which can be eliminated by repeating the simulations and interpolating the results.

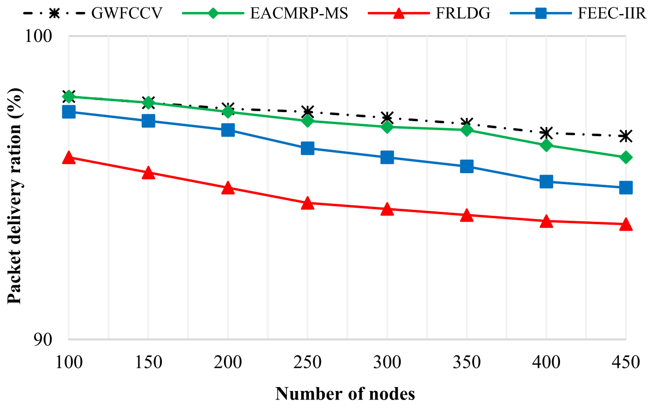

Fig. 5. Comparison of package delivery ratio in different methods.

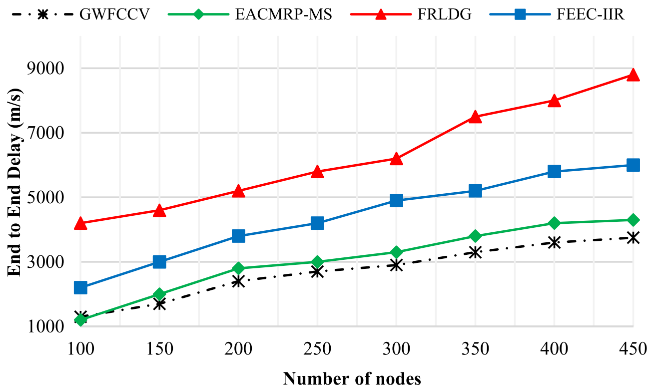

Fig. 6. End-to-end delay comparison of different methods.

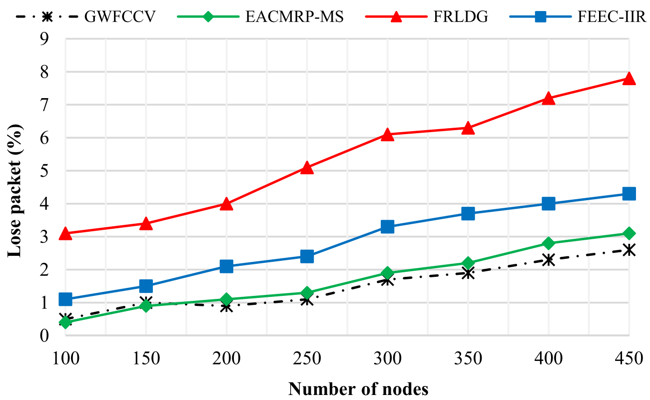

Fig. 7. Packet loss rate VS number of nodes.

5.6. *Lifetime of network*

Considering the optimal performance of the proposed method in terms of evaluated parameters compared to other methods, it is possible to see the improvement of the network lifetime in the proposed method in Fig. 8 compared to other methods. As can be seen in Fig. 8, for <300 nodes, in the proposed method, the lifetime of the network has improved more than other methods. When the number of nodes is >300, Performance of the proposed method in terms of network lifetime is near to the EACMRP-MS, but still outperforms this method and other methods. Table 9 shows the comparison of the improvement percentages of the proposed method in terms of different parameters compared to other methods.

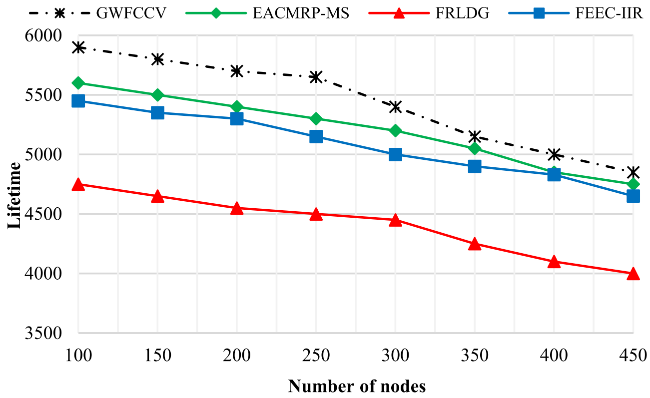

Fig. 8. Network lifetime VS number of nodes.

Table 9
Percentage improvement over other methods.

	EACMRP-MS	*FEEC-IIR*	*FRLDG*
Throughput	7.07 %	14.83 %	36.4 %
Lifetime	5.43 %	8.3 %	23.26 %
PDR	2 %	3.5 %	4.5 %
E2E delay	11.99 %	38.32 %	56.96 %
Energy consumption	14.26 %	31.83 %	53.56 %
Packet lose	12.41 %	46.43 %	72.09 %

5.7. Time and space complexity analysis of the proposed method

Time complexity refers to the computational complexity that describes the amount of time an algorithm takes to run as a function of the length of the input. It gives an estimate of the number of basic operations or steps an algorithm must perform relative to the size of the input data. Time complexity is typically expressed using Big O notation, which focuses on the worst-case scenario by showing how the runtime grows asymptotically as the input size increases. To calculate time complexity, we analyze the loops, recursive calls, or any iterative process in the algorithm to determine how many times the fundamental operations are executed relative to the input size n. For example, an algorithm with time complexity $O(n^2)$ means that the runtime grows quadratically with the size of the input. Space complexity refers to the amount of memory an algorithm requires to run as a function of the input size. It accounts for both the memory used by the algorithm itself (such as variables and data structures) and any additional memory required for processing the input. Similar to time complexity, space complexity is expressed using Big O notation, which focuses on how the memory usage grows relative to the input size n. To calculate space complexity, we analyze the variables, arrays, recursion depth, and data structures used in the algorithm. For example, an algorithm with space complexity $O(n)$ means that the memory required grows linearly with the size of the input. Space complexity is crucial for evaluating how efficiently an algorithm manages memory, particularly for large datasets. Our proposed hybrid algorithm combines Fuzzy C-Means (FCM) and Grey Wolf Optimizer (GWO) for improved clustering in wireless sensor networks. The FCM initializes cluster centers, which are then optimized by GWO to enhance clustering quality. The time complexity for FCM is $O(n{\cdot}k{\cdot}t)$, while GWO has a time complexity of $O(m{\cdot}t{\cdot}k)$, where n is the number of nodes, k is the number of clusters, t is the number of iterations, and m is the population size of wolves. Space complexities are $O(n{\cdot}k)$ for FCM and $O(m{\cdot}k)$ for GWO. The CRITIC method, used for dynamic weighting, and Fuzzy VIKOR, applied for route selection, each have time and space complexities of $O(n{\cdot}c)$, where c is the number of criteria. The overall time complexity of our hybrid approach is $O((n+m){\cdot}k{\cdot}t)$, and the space complexity is O

Table 10
Time complexity of the compared methods.

Method	Time Complexity	Explanation
FRLDG	$O(n{\cdot}\log n)$	Due to fuzzy logic-based routing and Harris Hawk Optimization (HHO) for path selection, which is efficient for clustering and routing tasks.
EACMRP-MS	$O(n^2)$	Involves Tunicate Swarm Algorithm (TSA) for cluster formation and multi-hop routing, resulting in higher computational demand.
FEEC-IIR	$O(n{\cdot}m)$ or $O(n^2)$ depending on ACO usage	Uses Water Strider Algorithm (WSA) for clustering and Ant Colony Optimization (ACO) for route optimization, leading to moderate to high complexity.
GWFCCV	$O((n+m){\cdot}k{\cdot}t)$	Our proposed hybrid algorithm combines Fuzzy C-Means (FCM) and Grey Wolf Optimizer (GWO) for improved clustering in wireless sensor networks. Also, the CRITIC method, used for dynamic weighting, and Fuzzy VIKOR, applied for route selection.

$((n + m) \cdot k)$. This analysis highlights that our algorithm is scalable and can be efficiently applied to large-scale networks, with complexity growing linearly with the number of nodes and clusters. Table 10 shows the overall time complexity of all compared methods. n represents the number of sensor nodes and m represents the number of cluster heads.

6. Conclusion

In this research, we introduced a hybrid routing approach named GWFCCV, designed to optimize network performance in IoT environments utilizing Wireless Sensor Networks (WSN). The proposed method combines the strengths of Fuzzy C-Means (FCM) and Gray Wolf Optimizer (GWO) to create efficient clustering, enhancing both stability and energy efficiency. By integrating the CRITIC and Fuzzy VIKOR methods for multi-criteria decision making, our approach ensures optimal routing decisions by effectively ranking nodes based on their residual energy, throughput, and memory capacity. The simulation results illustrate significant improvements in energy consumption, throughput, and network lifetime compared to other state-of-the-art methods. For the Throughput parameter, the GWFCCV method achieved improvements of 7.07 %, 14.83 %, and 36.4 % compared to EACMRP-MS, FEEC-IIR, and FRLDG, respectively. In Energy consumption, the improvements achieved by GWFCCV were 14.26 %, 31.83 %, and 53.56 %, and finally, in lifetime, the improvements were 5.43 %, 8.3 %, and 23.26 % over the three mentioned methods. Future research will explore incorporating machine learning techniques to make clustering and routing more adaptive and resilient in dynamic environments, extend the algorithm for use in larger and more heterogeneous IoT networks, and integrate security measures to protect against cyber-attacks, which are critical for IoT systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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