Energy and Distance Aware Clustering-Based Routing for Low-Power IoT-Enabled Wireless Sensor Networks

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Abstract. The ever-increasing demand for Internet of Things (IoT) applications leads to the deployment of a massive amount of devices in wireless sensor networks (WSNs). The IoT-enabled WSNs suffer from the problems of often non-rechargeable, non-replaceable, and limited battery sources of sensing devices, namely low-power IoT-enabled WSNs. This paper addresses these problems by proposing an energy and distance aware clustering-based routing (EDCR) method. Particularly, in the clustering phase, a fuzzy-assisted K-means clustering (FKMC) technique is applied to ensure that the distribution of sensors in all clusters is similar and the cluster heads have enough energy resources to communicate with the base station (BS). In the routing phase, a fuzzy-assisted ant colony based routing (FACR) algorithm is deployed to find the optimal paths from the source sensors to the BS by identifying the intermediate sensors based on the residual energy for communications, the distance from the current sensor to the following one, and the distance from the follower to the BS. As a result, the proposed EDCR method can balance the workload of sensors among clusters by FKMC to significantly enhance the energy efficiency for low-power IoT-enabled WSNs by FACR compared to other conventional schemes.

Keywords: Ant Colony based Routing · Clustering-based Routing · Energy-aware Routing · Fuzzy Logic Model · Internet of Things · K-means Clustering · Wireless Sensor Networks

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1 Introduction

Internet of Things (IoT)-enabled wireless sensor networks (WSNs) represent a system comprising numerous sensors and data collection nodes distributed sporadically within an observation area [1]. These sensors can gather information about the surroundings (e.g., temperature, humidity, light, vibration etc.), surveillance, and public safety. Subsequently, this information is converted into proper data structures and transmitted to the base station (BS) or the central node for analysing, making decisions, and other future research purposes [2]. IoT-enabled WSNs have become the key research area in the fields of information systems and artificial intelligence, and widely applied to various practical applications and services, from environmental monitoring, resource and natural disaster management, to smart cities [3–6].

In IoT-enabled WSNs, the sensing devices are often non-rechargeable, non-replaceable, and limited battery sources. Therefore, the so-called low-power IoT-enabled WSNs always require disruptive clustering and routing techniques which have drawn a significant attention from the researchers and experts in both the industrial and academic sectors, to enhance the energy efficiency of sensing devices, and thus optimize the network operations. Clustering techniques organize the sensors into different clusters, each has a cluster head (CH), for collecting and processing data. This way balances the energy distribution within clusters for preventing from the overload situation to ensure high energy efficiency. As a result, the data processing capability at the CHs is enhanced, thereby boosting the network throughput. This not only helps minimize the energy consumption of sensors but also improve the system's lifespan, capacity, and scalability [7–15]. Meanwhile, routing techniques ensure efficient data transmission from the source sensors to the destination ones. Optimizing the communication paths can further minimize the energy consumption during transmission, enhance the communication effectiveness, and finally prolong the lifespan of system.

The integration of clustering and routing techniques can significantly provide the low-power IoT-enabled WSNs with flexible and efficient management, optimize the system resources, ensure the reliability of data [16,17], and meet the ever-growing demands for various advanced applications and services [18]. However, designing energy-saving solutions for clustering and routing techniques is the major challenge [10] due to limited communication ranges and harsh operating environments. In addition, managing the sensors and CHs and determining the best paths are also challenging for optimizing the performance of IoT-enabled WSNs [9].

In this paper, we apply the K-mean technique to cluster the sensors in the system with the initial number of clusters chosen from the LEACH [19]. Next, we utilize a fuzzy logic model to assist the K-mean clustering technique, namely fuzzy-assisted K-means clustering (FKMC) technique, to determine the new CHs for each cluster, using two crucial parameters of residual energy and distance to the BS. Furthermore, we employ the ant colony (ACO) routing algorithm to find the optimal path from the sensors to the BS. Again, we use the fuzzy logic model to assist the ACO routing algorithm, namely fuzzy-assisted ACO based routing

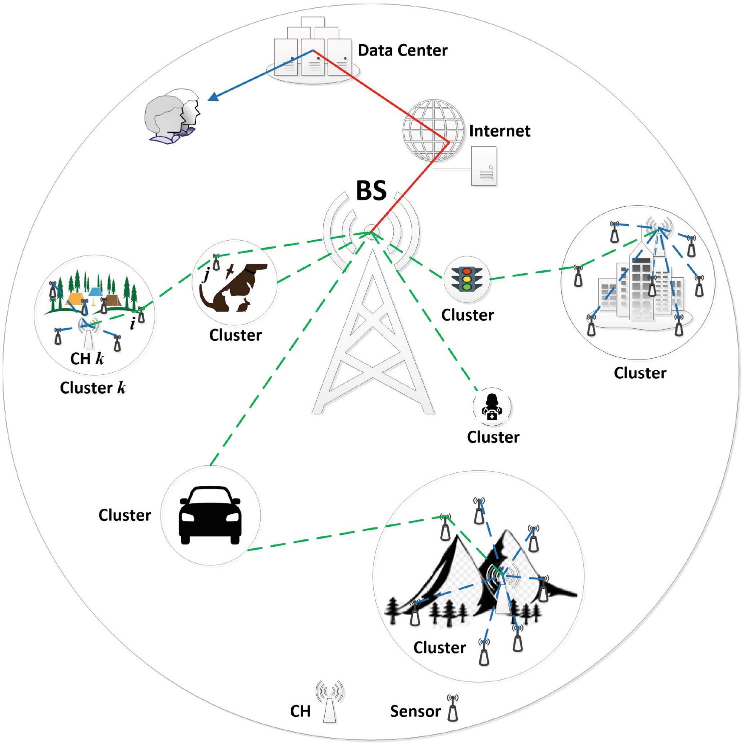

Fig. 1. IoT-enabled WSNs

(FACR), for finding the best path to the BS. The selection of intermediate sensors to forward the data to the BS is based on two key parameters of the residual energy for communications and the distances, i.e., distance from the current sensor to the following sensor and distance from the following sensor to the BS. By combining the strengths of FKMC and FACR, we propose an energy and distance aware clustering-based routing (EDCR) method to enhance the performance of IoT-enabled WSNs.

The rest of this paper is organized as follows. We introduce the system model of IoT-enabled WSNs and describe how it works in Sect. 2. The FKMC technique and FACR algorithm of EDCR method are presented in Sect. 3 and Sect. 4, respectively. In Sect. 5, we show the simulation results to demonstrate the benefits of the proposed EDCR compared to other conventional schemes. Finally, the paper is concluded in Sect. 6.

2 System Model

2.1 Clustering and Routing Model

We consider a system of IoT-enabled WSNs as illustrated in Fig. 1. The system comprises N sensors grouped into K clusters, one BS, and a data processing center. Each cluster has one cluster head (CH). In this system, if an arbitrary sensor in the cluster k, $k = 1, 2, ..., K$, has enough energy, it can send the data directly to the BS. Otherwise, it sends the data to the CH k. Then, the CH k selects one of its neighbors, i.e., sensor i. After that, the sensor i finds the following sensor j in the next cluster to continuously forward the data. In this next cluster, the progress repeats in the same manner with the cluster k until the data is sent to the BS. Obviously, the CHs can send the data directly to the BS depending on the routing results. To do so, the BS has to collect the information of energy resources and locations of all the sensors. To optimise the energy consumption during the transmission from any sensor to the BS, the BS conducts two phases: 1) clustering phase and 2) routing phase presented as follows.

- **Clustering phase:** In this phase, there are two steps including clustering and CH selection using FKMC technique. First, K-means clustering technique is applied to divide N sensors into K clusters. The centroids of all clusters are fine-tuned to ensure their operational range is similar. This way, the density of sensors in the system is evenly distributed within each cluster, and thus minimise the deviation of sensor numbers among different clusters. As a result, the system can operate more efficiently in terms of energy consumption (or workload) balance. Second, we apply a fuzzy logic model to select the CHs to ensure that they can collect the data from their members and transmit it to the BS. The fuzzy logic considers not only the distance between the CHs and the BS but also the remaining energy resources of the CHs, to ensure that the CHs are capable of performing their role, i.e., ensuring the reliability in data collection and transmission.
- **Routing phase:** In routing phase, we apply the FACR algorithm to establish the paths from arbitrary sensors to the BS for data transmission. During this phase, the ants need to utilise a fuzzy logic model by incorporating two essential factors of distances (from the sensor i to the sensor j and from the sensor j to the BS) and the energy consumption of the sensor i. Thanks to the intelligent selection of the next sensors by the ants, the energy is efficiently utilised to prolong the system operation lifetime.

After completing the clustering and routing phases, the system goes to the transmission phase with the transmission energy consumption model presented in the sequel.

2.2 Transmission Energy Consumption Model

To transmit a packet of length b bits over a distance d, we apply the transmission energy consumption model given in [19,20]. The energy consumption of a transmit (Tx) sensor is expressed as

$$E_{Tx}(b,d) = b \times \big(E_e + E_a(d)\big) = \begin{cases} b \times (E_e + \varepsilon_{fs} \times d^2), d < d_0, \\ b \times (E_e + \varepsilon_{mp} \times d^4), d \geq d_0, \end{cases} \tag{1}$$

where E_e is the energy dissipated for transmit electronics, $E_a(d)$ is the energy consumption for transmit amplifier, ε_{fs} and ε_{mp} are the quantities required for the transmit amplifiers to achieve an acceptable energy per bit to the spectral noise density respectively in free space and multipath propagation models, and d_0 is the reference distance for transmission mode selection in the system given by

$$d_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mp}}}. \tag{2}$$

At the receive (Rx) sensor, the energy dissipated for receiving b bits is expressed as

$$E_{Rx}(b) = E_e \times b. \tag{3}$$

3 FKMC Technique

The FKMC technique includes four steps: preparing the data for analysis, choosing the number of initial CHs, updating the cluster centers, and CH selection. The details of FKMC technique are presented as below.

3.1 Preparing the Data for Analysis

Given a set of N sensors, located at $X = [x_1, x_2, ..., x_n, ..., x_N] \in \mathbb{R}^{2\times N}$ and $K < N$ is the initial number of clusters. We must find the cluster centers $m_1, m_2, ..., m_k, ..., m_K \in \mathbb{R}^{2\times K}$ and assign the labels to each sensor. For each sensor x_n, we define a label vector $y_n = [y_{n1}, y_{n2}, ..., y_{nK}]$. Here, if x_n is assigned to the k^{th} cluster, then $y_{nk} = 1$, otherwise $y_{nk} = 0$.

3.2 Choosing the Number of Initial Clusters

In order to create K clusters, every sensor generates a random value in the range of [0, 1]. If the value of the sensor n is less than the threshold $T(r, n)$, this sensor becomes a temporary CH in the current round r, and thus we totally have K_r CHs. The threshold $T(r, n)$ is given by [19]

$$T(r,n) = \begin{cases} 0, & n \in \mathcal{G}(r-1), \\ \frac{p}{1-p\left(r \bmod \frac{1}{p}\right)}, & n \notin \mathcal{G}(r-1), \end{cases} \tag{4}$$

where p is the desired percentage of the active sensors in the system to become the CHs, $\mathcal{G}(r-1)$ is the set of CHs selected in the previous round $(r-1)$. The CHs are re-selected after each round to distribute the workload evenly. The initial centroids m_k, $k = 1, 2, ..., K_r$, are defined as the locations of the CHs.

3.3 Updating the Cluster Centers

In the round r, the sensor i belongs to the cluster k if $k = \arg\min ||x_i - m_{r,l}||^2, l = 1, 2, ..., K_r$. This also enables us to obtain the number of sensors $N_{r,k}$ of the cluster k. Then, the new centroid of the cluster k is given by

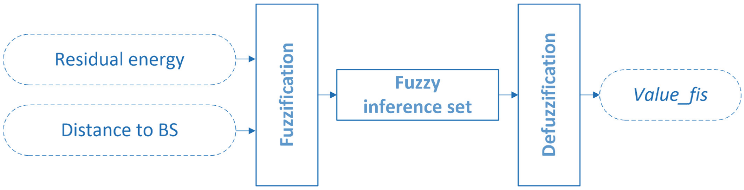

Fig. 2. Fuzzy-based CH Selection.

Table 1. Fuzzy Clustering Linguistic Variable

Input Parameter	Linguistic Value
Residual energy	Scant, Medium, Abundant
Distance to BS	Close, Mean, Far

$$m_{r,k} = \frac{1}{N_{r,k}} \sum_{i=1}^{N_{r,k}} x_i. \tag{5}$$

The process of updating the cluster centers repeats until a termination condition is met, i.e., the $m_{r,k}$ and the members in the cluster k are not changed any more.

So far, we obtain the clustering results including the cluster center of cluster k and its members $N_{r,k}$. We use the standard deviation to measure the level of dispersion of sensors within each cluster, expressed as

$$\sigma_r = \sqrt{\frac{\sum_{k=1}^{K_r} (N_{r,k} - 1 - \mu_r)^2}{K_r}}, \tag{6}$$

where

$$\mu_r = \frac{\sum_{k=1}^{K_r} N_{r,k} - K_r}{K_r}. \tag{7}$$

3.4 Fuzzy-Based CH Selection

Unlike LEACH and LEACH-C, we apply fuzzy logic to the CH selection process. The structure of the fuzzy model for CH selection in FKMC technique is illustrated in Fig. 2. The input data, i.e., residual energy and distance to BS, is transformed through a fuzzification, resulting in fuzzy values represented by the respective membership functions μ_{ReE} and μ_{D2B}. The outcome of the fuzzification process is the assistance of fuzzy rule bases, where linguistic variables are used and combined. The set of output results is represented in fuzzy values, thus they need to be converted to crisp values ($Value\_fis$) for the use in the CH selection process. This is achieved through the defuzzification process.

Linguistic Variables for CHs: The optimal selection of linguistic variables for the system can enhance the lifespan performance. The input parameters of the fuzzy-based CH selection are presented in Table 1.

- **Residual Energy**
  Energy plays a crucial role in WSNs. The sensors need sufficient energy to transmit (receive) data to (from) each other. As specialized sensors, CHs are responsible for gathering information from the others and transmitting it to the BS. Therefore, residual energy is indispensable in the process of selecting CHs. Let ReE be the linguistic variable for residual energy with the base variable u, it belongs to the defined domain $U = [0, 0.1]$. The set of linguistic values are $T(ReE) = \{Scant, Medium, Abundant\}$ corresponding to three fuzzy sets represented by the membership functions $\mu_{Scant}(u)$, $\mu_{Medium}(u)$ and $\mu_{Abundant}(u)$ defined as

$$\mu_{Scant}(u) = \begin{cases} 1 & if\ 0 \leq u \leq 0.02 \\ \frac{0.05-u}{0.03} & if\ 0.02 < u \leq 0.05 \\ 0 & if\ u < 0, u > 0.05 \end{cases} \tag{8a}$$

$$\mu_{Medium}(u) = \begin{cases} \frac{u-0.02}{0.03} & if\ 0.02 \leq u < 0.05 \\ 1 & if\ u = 0.05 \\ \frac{0.08-u}{0.03} & if\ 0.05 < u \leq 0.08 \\ 0 & if\ \ u < 0.02, u > 0.08 \end{cases} \tag{8b}$$

$$\mu_{Abundant}(u) = \begin{cases} \frac{u-0.05}{0.03} & if\ 0.05 \leq u < 0.08 \\ 1 & if\ 0.08 \leq u \leq 0.1 \\ 0 & if\ u < 0.05, u > 0.1 \end{cases} \tag{8c}$$

- **Distance to BS**
  Distance is a crucial factor in selecting the proper CHs. Let $D2S$ be the linguistic variable representing the distance to the BS with the base variable u taken from the defined domain $U = [0{,}100]$. $D2S$ is divided into three main linguistic values of $Close$, $Mean$, and Far, corresponding to three fuzzy sets respectively in the ranges of [0, 50], [20, 80], and [50, 100]. The membership functions $\mu_{Close}(u)$, $\mu_{Mean}(u)$, and $\mu_{Far}(u)$ are expressed as

$$\mu_{Close}(u) = \begin{cases} 1 & if\ 0 \leq u \leq 20 \\ \frac{50-u}{30} & if\ 20 < u \leq 50 \\ 0 & if\ u < 0, u > 50 \end{cases} \tag{9a}$$

$$\mu_{Mean}(u) = \begin{cases} \frac{u-20}{30} & if\ 20 \leq u \leq 50 \\ 1 & if\ u = 50 \\ \frac{80-u}{30} & if\ 50 < u \leq 80 \\ 0 & if\ u < 20, u > 80 \end{cases} \tag{9b}$$

$$\mu_{Far}(u) = \begin{cases} \frac{u-50}{30} & if\ 50 \leq u < 80 \\ 1 & if\ 80 \leq u \leq 100 \\ 0 & if\ u < 50, u > 100 \end{cases} \tag{9c}$$

Table 2. The fuzzy rules of FKMC

Residual energy	Distance to BS		
	Close	Mean	Far
Scant	Average	Low	Very low
Medium	Strong	Average	Very low
Abundant	Very strong	Strong	Low

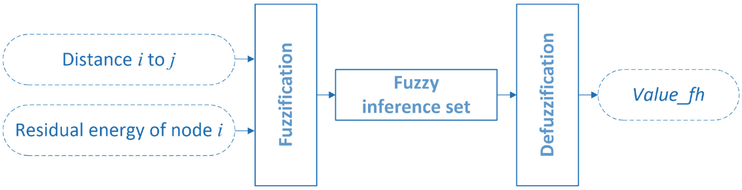

Fig. 3. Fuzzy heuristic model of FACR.

Membership Function for CHs: The general formulas for the fuzzy sets of ReE and $D2B$ can be expressed as

$$\mu_{ReE}(u) = \{\mu_{Scant}(u), \mu_{Medium}(u), \mu_{Adundant}(u)\}, \tag{10}$$

and

$$\mu_{D2B}(u) = \{\mu_{Close}(u), \mu_{Mean}(u), \mu_{Far}(u)\}, \tag{11}$$

where $\mu_{Scant}(u)$, $\mu_{Medium}(u)$ and $\mu_{Abundant}(u)$ represent the degree to which u belongs to the respective set of "Scant", "Medium" and "Abundant", while $\mu_{Close}(u)$, $\mu_{Mean}(u)$, and $\mu_{Far}(u)$ indicate the extent to which u is a member of the corresponding categories "Close", "Mean", and "Far".

Fuzzy Logic Rule Base for CHs: Fuzzy rule base plays a crucial role in the fuzzy model of CH selection. It consists of the rules applied to make the decisions based on two linguistic variables ReE and $D2B$, along with the corresponding membership functions μ_{ReE} and μ_{D2B}. According to [21], the "And" operation is employed to combine the fuzzy values of the two input linguistic variables. This results in fuzzy rules described in Table 2.

4 FACR Algorithm

To ensure the data transmission from the source to the destination is of utmost importance of FACR. The FACR algorithm integrates the heuristic ACO based routing with fuzzy technique to address the drawbacks of both the LEACH and LEACH-C algorithms. This finds the optimal path from one sensor to another

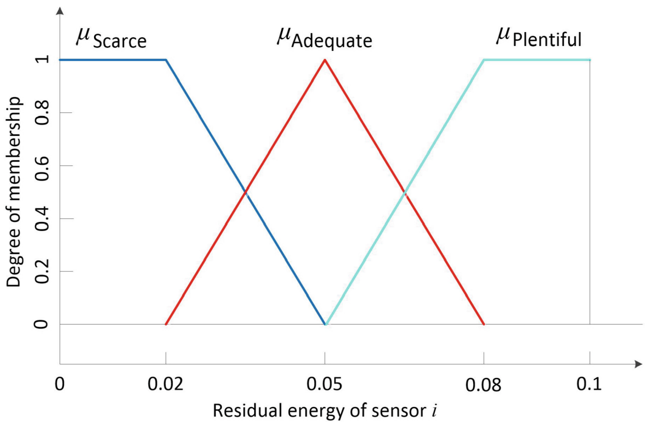

Fig. 4. The membership function of the linguistic variable Pos.

and finally to the BS. Although the ACO method may require complex computations and significant resources, especially when dealing with many sensors, it provides a crucial benefit of searching for an optimal solution across the entire search space without getting stuck at local optimal solutions.

4.1 Fuzzy Heuristic Model for Routing

In FACR algorithm, heuristic information is utilized for finding the optimal path from the source sensor to the BS. Ants rely on the heuristic information to guide themselves in selecting the next sensor while searching for the optimal way. In the proposed FACR algorithm, the heuristic information is called a fuzzy heuristic. The fuzzy heuristic encompasses the factors such as the residual energy and the distances from the source sensor to the following one and from the follower to the BS, to ensure the communications between them. These factors serve as the input variables for the fuzzy heuristic model as shown in Fig. 3. This fuzzy heuristic model produces a distinct output value named $Value\_fh$, representing the FACR solution's heuristic information to guide the ants. The next chosen potential sensor, which must possess a proper set of distance and energy or a superior $Value\_fh$ compared to its candidates, is presented below.

To assess the possibility of data transmission at the sensor i in the cluster k, we must consider both the distance and the residual energy during data transmission. Here, the distance includes $d(i,j)$ (distance from the sensor i to the following sensor j) and $d(j,\mathrm{BS})$ (distance from the sensor j to the BS). The possibility is given by

$$Pos_{ij} = \frac{E_i}{d(i,j) \times d(j,\mathrm{BS})}. \tag{12}$$

In (12), Pos_{ij} is a linguistic variable describing the residual energy of the next sensors, with the base variable v belonging to the defined domain $V =$

[0, 0.1]. The set of linguistic values $T(Pos) = \{Scarce, Adequate, Plentiful\}$ corresponds to three fuzzy sets with defined ranges [0, 0.05], [0.02, 0.08], and [0.05, 0.1]. The membership functions $\mu_{Scarce}(v)$, $\mu_{Adequate}(v)$, and $\mu_{Plentiful}(v)$ are illustrated in Fig. 4.

4.2 ACO Based Routing

Based on the fuzzy heuristic model for routing, the operation of FACR algorithm, which consists of 5 steps, is presented in the sequel.

- **Step 1 - Initializing the Heuristic Knowledge:** In this step, each ant is equipped with the heuristic knowledge before embarking on the search for the path to the BS. This knowledge is pre-computed based on the $Value\_fh$ value from the fuzzy heuristic model.
- **Step 2 - Initiating the Search:** The ants are randomly deployed within the network, starting from the source sensors. Each ant decides its next sensor based on the fuzzy heuristic information and the level of pheromone marking on the edges. This fuzzy heuristic information guides the ant towards the sensors with higher potential.
- **Step 3 - Updating the Pheromone Marks:** After an ant completes its route, the pheromone mark (13) on the edges is updated based on the length of the path between two sensors. The ants traversing shorter edges will leave behind more pheromones. In the subsequent iterations, the heuristic knowledge is used to guide the ants to the next sensors (14). The ants continue moving through the sensors until they reach the destination or a stopping condition is met [22].

$$\tau_{ij} = \rho \times \tau_{ij} + \Delta\tau_{ij} \tag{13}$$

where:
  - τ_{ij} is the pheromone mark from the sensor i to the sensor j
  - ρ is the coefficient in the range of [0, 1] such that $(1-\rho)$ is the evaporation level.
  - $\Delta\tau_{ij} = \sum_{l=1}^{L} \Delta\tau_{ij}^{l}$ is the new contribution of pheromone added, calculated based on the quantity per unit of length that the ant l has traversed, i.e., L is the total number of ants. The likelihood of selecting the edge from the sensor i to the sensor j is denoted as [22,23]

$$P_{ij}^{l} = \begin{cases} \frac{(\tau_{ij})^{\alpha} \times (h_{ij})^{\beta}}{\sum_{l \in \{M \setminus V_l\}} (\tau_{il})^{\alpha} \times (h_{il})^{\beta}}, \text{if} j \in \{M \setminus V_l\}, \\ 0, \text{otherwise} \end{cases} \tag{14}$$

  where, $h_{ij} = \frac{1}{d_{ij}}$ is the heuristic value from the sensor i to the sensor j, M is the number of nodes (places), V_l is the number of the places visited by the ant l, and α and β are the parameters used to control the influence of the pheromones and the heuristics.

- **Step 4 - Choosing the Best Path:** After all the ants have completed the searching process, the optimal path is selected based on its optimal length or degree.
- **Step 5 - Updating the Overall Pheromone Marks:** The pheromone marks on all the edges are updated based on the length of optimal path.

Table 3. Simulation Parameters

Parameter	Value
N	100 sensors
p	5%
b	4000 bits
E_e	50nJ/bit
ε_{fs}	10pJ/bit/m^2
ε_{mp}	0.0013pJ/bit/m^4
r	1000 rounds
$\{\alpha, \beta\}$	$\{1, 2\}$
ρ	0.5
L	50

5 Performance Evaluation

In this section, we evaluate the performance of FKMC technique, FACR algorithm, and EDCR method. The simulation parameters are listed in Table 3. The sensors are deployed within a circle area of radius 50 m. All the sensors are with an initial energy of 0.1 J. To evaluate the simulation results, we compare FKMC, FACR, and EDCR to the well-known LEACH and LEACH-C schemes based on the performance metrics including standard deviation of sensor numbers among different clusters, residual energy, and number of active sensors in each round.

We first evaluate the benefit of FKMC technique in the clustering phase which provides the even distribution of sensors among different clusters. Comparing to LEACH, the FKMC results in a much smaller standard deviation of number of sensors as presented in Table 4 and Fig. 5. We can see that the higher discrepancy in the number of sensors among clusters certainly causes a worse workload balance, i.e., sensors in some clusters have to work more heavily than the others. This leads to imbalanced energy consumption and may reduce the lifespan of system. To further evaluate the performance of FKMC, we deploy the FKMC-assisted LEACH (FKMC-LEACH) and compare it to LEACH and LEACH-C as shown in Fig. 6. It is clear that FKMC-LEACH outperforms the others in terms of residual energy to enhance the lifespan of system thanks to the benefit of FKMC.

Table 4. Standard deviation of number of sensors

Solution	Number of Sensors in Clusters										Standard Deviation	Round
Cluster	1^{st}	2^{nd}	3^{rd}	4^{th}	5^{th}	6^{th}	7^{th}	8^{th}	9^{th}	10^{th}		
LEACH	63	19	15								**21.75**	1^{st}
FKMC	34	29	34								**2.35**	
LEACH	38	14	10	11	3	11	6				**10.63**	11^{st}
FKMC	21	14	14	6	12	14	12				**4.09**	
LEACH	56	12	12	16							**18.55**	21^{st}
FKMC	29	26	19	22							**3.81**	
LEACH	43	36	18								**10.53**	31^{st}
FKMC	27	36	34								**3.85**	
LEACH	33	10	17	13	22						**8.08**	41^{st}
FKMC	11	22	20	24	18						**4.47**	
LEACH	16	7	7	11	5	16	15	4	3	6	**4.81**	51^{st}
FKMC	10	10	12	7	3	10	11	9	6	12	**2.72**	
LEACH	51	26	20								**13.42**	61^{st}
FKMC	30	35	32								**2.05**	
LEACH	69	16	12								**25.98**	71^{st}
FKMC	28	25	44								**8.34**	
LEACH	23	26	8	8	17	12					**6.99**	81^{st}
FKMC	17	20	11	14	12	20					**3.59**	
LEACH	19	10	7	11	13	12	7	13			**3.61**	91^{st}
FKMC	12	11	9	10	14	12	10	14			**1.73**	

In Fig. 7, we evaluate the performance of EDCR, LEACH and LEACH-C in terms of the number of active sensors versus r. Obviously, more sensors become inactive when r increases. LEACH-C is always better than LEACH. Considering EDCR, some sensors start to be inactive earlier than that of LEACH-C, but then, i.e., after the 260^{th} round, the number of active sensors of EDCR is higher than that of LEACH-C. This results in the residual energy of EDCR outperforming the others to enhance the lifespan of system as shown in Fig. 8. Comparing FKMC-LEACH and EDCR, thanks to the benefit of both FKMC and FACR assisted, EDCR provides higher residual energy than FKMC-LEACH does in Fig. 6.

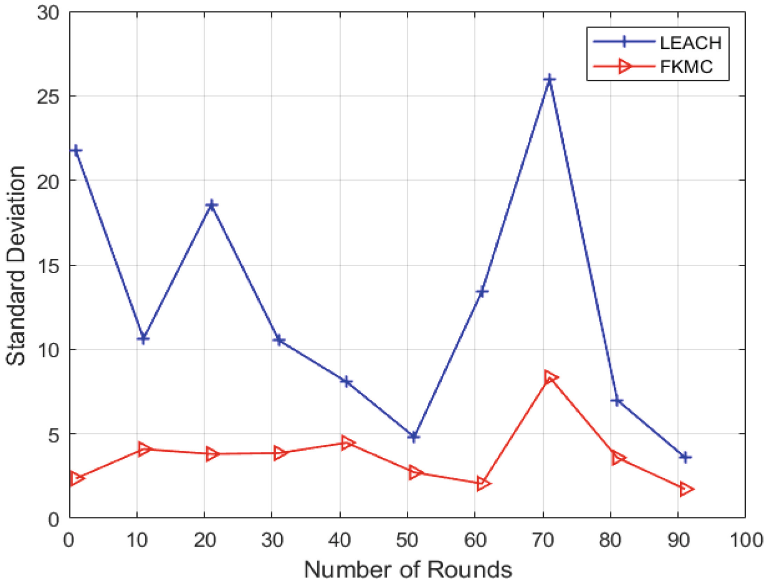

Fig. 5. Standard deviation of number of sensors

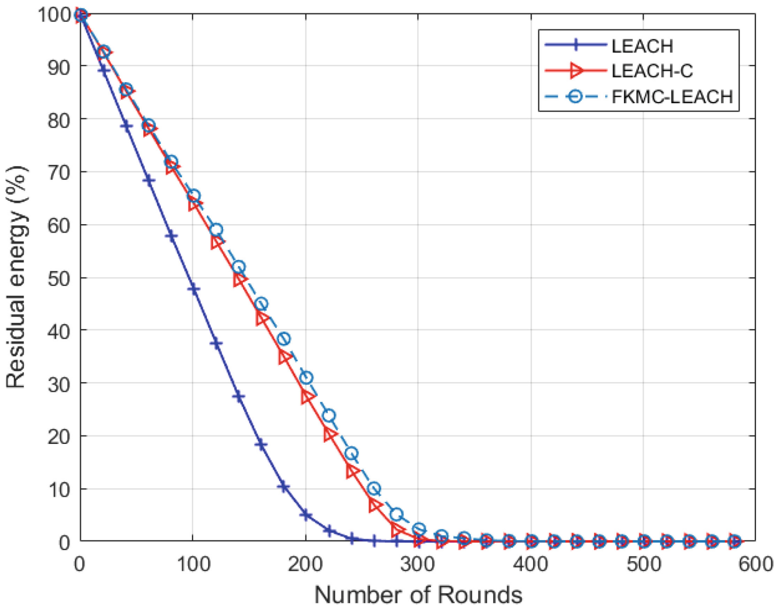

Fig. 6. Benefit of FKMC in terms of residual energy.

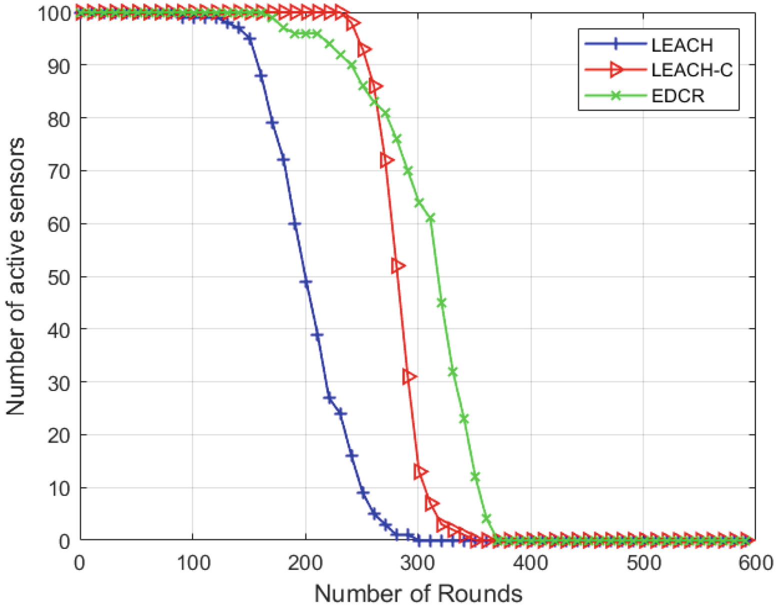

Fig. 7. Number of active sensors versus r.

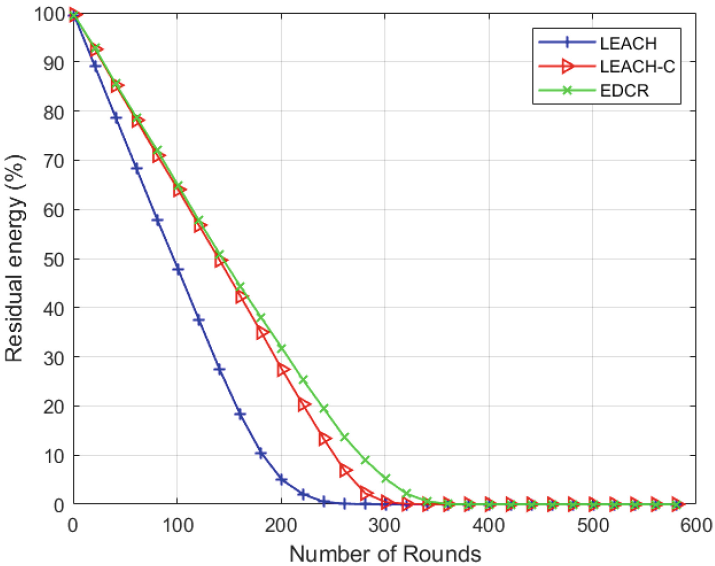

Fig. 8. Residual energy versus r.

6 Conclusion

In this paper, we have proposed the energy and distance aware clustering-based routing (EDCR) method that can efficiently conserve the energy resource for low-power IoT-enabled WSNs. The EDCR exploits the benefit of both fuzzy-assisted K-means clustering (FKMC) technique and fuzzy-assisted ant colony based routing (FACR) algorithm to balance the distribution of sensors in each cluster and further reduce the energy consumption. Simulation results are shown to demonstrate that the proposed EDCR outperforms the other conventional schemes, i.e., LEACH and LEACH-C without fuzzy logic model assisted, in terms of residual energy for the longer lifespan of low-power IoT-enabled WSNs.

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