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Fuzzy-GRA based Estimation of Data Collection Points for Mobile Data Collection in IoT-WSN

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***Abstract**— In Internet of Things (IoT) based Wireless Sensor Networks (WSN), during data collection from a Mobile Data Collector (MDC), the Data Collection Points (DCPs) should be selected based on various factors apart from required energy. The stopping time of MDC should be enough to collect data from all the nodes without increasing the data gathering delay. This work develops a Fuzzy-GRA based estimation technique of DCPs for MDC in IoT-WSN. In this technique, the Fuzzy-Grey Relational Analysis method is used for selecting the DCPs with maximum coverage, residual energy and buffer size. By simulation results, we show that the data redundancy is reduced, and energy is saved. By simulation results, it has been shown that the Fuzzy-GRA attains maximum delivery ratio of 0.96 and residual energy 24 joules with reduced data collection delay of 0.2 seconds.*

***Index Terms**— Internet of Things (IoT), Wireless Sensor Network (WSN), Mobile Data Collector (MDC), Data Collection Point (DCP), Fuzzy-Grey Relational Analysis (Fuzzy-GRA)*

I. INTRODUCTION

The advent of IoT, commonly referred to as the Internet of Things, will usher in a significant transformation in virtually every aspect of our lives. The Internet has an impact on humankind, as well as business, science, government, and education. The core concept of the IoT can be summed up as the promotion of communication across any devices, from any place, at any time. IoT is useful for creating smart cities, smart transit systems, smart industries, and a variety of other things. Anybody can access the IoT at any time, from any location, and everything will be connected (Christen et al 2013). Many applications for connecting things with the aid of the internet are provided by this recent and cutting-edge technology. They can communicate with other devices or service platforms via various networks (Kadam et al 2015)(Patel and Patel 2016). WSN is a crucial component of IoT where sensor nodes gather information by seeing the physical world and relay it to sink nodes utilizing multi-hop communication. The data collected by distributed sensor nodes in a WSN are collected at the sink node or base station (BS) (A1-Qurabat and Idrees 2020)

The process of integrating and summarizing data from sensor nodes in WSNs with the use of aggregation functions on aggregator nodes is known as data aggregation (A1-Qurabat and Idrees 2020). Data aggregation aims to eliminate redundant data transmissions and so increase network lifetime (Idrees and Al-Qurabat 2017). IoT data collecting WSN is crucial in the IoT because sending data requires more energy due to the heterogeneous data that is gathered from many sources (A1-Qurabat and Idrees 2018). Data gathering assists in compiling data from numerous sources. The goal of data aggregation techniques on the IoT is to achieve high QoS, which includes taking into account the priority of the data and having low data transmission latency, high dependability, and minimal energy consumption (A1-Qurabat and Idrees 2018).

The heterogeneity of the data in IoT is the major issue of data collection in IoT-WSN. The performance of MDC assisted data collection will be significantly impacted by the placement and clustering of sensors, as well as the choice of data collection mode (Fasolo et al 2007). The adaptability and ease of data collection in this network are increased by MDCs. In MDC problem, the DCPs should be selected based on various factors apart from the required energy level. In large-scale WSN systems, it is crucial and vital to create an effective trajectory planning strategy for MDCs. In MDC path planning problem, data aggregation must be completed in a short amount of time (Sangolgi et al 2013).

The major aim of this work is to select the data collection points (DCPs) for the MDCs, based on the network coverage, buffer capacity and energy levels of sensors. To meet this objective, Fuzzy-GRA based estimation of DCPs for MDC in IoT-WSN is proposed.

II. RELATED WORKS

This work presents a review of several data aggregation approaches and protocols conducted by Dehkordi et al. (2019). The ultimate goal of this study is to lay the fundamental foundations for the creation of new, cutting-edge designs based on data gathering techniques and clustering that have already been put forth.

Abdulsalam et al (2017) have explored the topic of enhancing the lifetime of sensors using a cluster based data gathering scheme. We suggest a fresh approach to solving the issue. In an IoT environment, Mobile Elements (ME) serve as Cluster Heads (CHs) in an algorithm for cluster-based aggregation. We think that combining IoT technology with WSN technology yields positive outcomes. Our tests

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demonstrate a substantial increase in network lifetime without affecting the accuracy of data collection.

Li et al. (2020) have introduced an innovative data collection architecture that allows a UAV to gather data from various IoT devices. Subsequently, in order to tackle the challenges of optimizing data collection from IoT devices at different hovering locations, they have formulated two maximization problems. To assess the coverage performance of IoT employing Mobile Data Collectors (MDCs), Ma et al. (2021) proposed an analytical framework. Within this framework, MDCs are modeled to follow a Simple Random Waypoint (SRWP) mobility pattern. They derived precise mathematical expressions for two key metrics which may serve to identify the interference pattern across the entire network.

III. PROPOSED METHODOLOGY

3.1. Overview

In this paper, Fuzzy-GRA method, which is useful for multiple attribute decision-making problems, is applied for estimation of DCPs. In this method, the network coverage, buffer size and residual energy metrics are considered as attributes with the weighting factors. Then, the sensor nodes with maximum coverage, residual energy and buffer size are selected as DCPs for collecting data from a set of neighboring sensors.

3.2. Parameter Estimation

The below points illustrates the brief details on selected parameters for data collection:

Network Coverage: Nodes with maximum network coverage should be selected in order to perform the data collection efficiently.

$$CP = P\,[SINR>G] \tag{1}$$

Buffer Size (V): A small amount of buffer space is available on the sensor nodes for caching transient data. If there is a delay indata collection, it may result in buffer overflow andloss of information. Hence, nodes with maximum buffer size should be considered.

$$V(n_i) = \{(1-(B(n_i\}/Bmax)\} \tag{2}$$

Residual Energy: Since, the distance is exactly proportional to the transmitted energy, the node with high energy level should be considered.

For a distance of (i, j), the energy required to transport a packet of length k-bits is given by:

$$E_{tx}(i,j) = \begin{cases} (ED + k \times u(i,j)^2 \times \gamma, if\ u(i,j) < u_0 \\ ED + l \times u(i,j)^4 \times \gamma, otherwise \end{cases} \tag{3}$$

Where ED is the energy dissipation in circuit, k is the energy dissipation in amplifier and circuit

The amount of energy used to receive a k-bit data packet is given as follows:

$$E_{rx} = ED{*}\gamma \tag{4}$$

$$E_{res} = E_{tx} - E_{rx} \tag{5}$$

3.3. Grey relational analysis (GRA) method

This approach, initially developed by (Deng 2010), has proven to be highly effective in resolving various decision making problems. The core procedure of GRA begins with the transformation of the performance of all available options into a sequence that allows for comparison. The Grey Relational Coefficient (GRC) between each source and the optimal target sequence is then computed. At the final stage, the GRCs estimate the Grey Relational Degree (GRD) between the optimal target and each source sequence.

3.4. Fuzzy-GRA Method

Let G_1, G_2 and G_3 be the Network Coverage, Buffer size and Residual Energy respectively. Let W_1, W_2 and W_3 be corresponding weight factors of the defined attributes. Let A_1, A_2 and A_3 be the discrete set of alternatives. Let α_1 , α_2 and α_3 are the degrees for satisfying the constraints G_1, G_2 and G_3 given by the decision maker respectively. Let b_1 , $b$and b_3 are the degrees for not satisfying the constraints G_1, G_2 and G_3 given by the decision maker respectively. Let q be the identification coefficient and S be the set of weight information.

The steps involved in this method are as follows (Chang 2021):

1. Positive (I^{+ve}) and Negative Ideal Solution (I^{-ve}) needs to be determined based on the intuitionistic fuzzy numbers.

$$I^{+ve} = ((\alpha_1^+, b_1^+), (\alpha_2^+, b_2^+), (\alpha_3^+, b_3^+)) \tag{6}$$

$$I^{-ve} = (\alpha_1^-, b_1^-),\ (\alpha_2^-, b_2^-), (\alpha_3^-, b_3^-) \tag{7}$$

Where $I_j^{+ve} = (\alpha_j^+, b_j^+) = (max_i \alpha_{ij,} min_i b_{ij})$, j = 1,2 ,3..n

$I_j^{-ve} = (\alpha_j^-, b_j^-) = (min_i \alpha_{ij,} max_i b_{ij})$, j = 1,2 ,3..n

2. From I^{+ve}, each alternative's GRC will be calculated by:

$$C_{ij}^{+ve} = \frac{min_i min_j d(\widetilde{I_{ij}}, I_j^{+ve}) + q max_i max_j d(\widetilde{I_{ij}}, I_j^{+ve})}{d\left(\widetilde{I_{ij}}, I_j^{+ve}\right) + q max_i max_j d(\widetilde{I_{ij}}, I_j^{+ve})}$$

i = 1, 2, … ,x. (where $1 \le i \le x$) (8)

j = 1,2,…, y. (where $1 \le j \le y$)

q = 0.5

3. The GRC of each alternative is computed from I^{-ve} as follows:

$$C_{ij}^{-ve} = \frac{min_i min_j d(\widetilde{I_{ij}}, I_j^{-ve}) + q max_i max_j d(\widetilde{I_{ij}}, I_j^{-ve})}{d\left(\widetilde{I_{ij}}, I_j^{-ve}\right) + q max_i max_j d(\widetilde{I_{ij}}, I_j^{-ve})}$$

i = 1, 2, … ,x. (where $1 \le i \le x$) (9)

j = 1, 2, …, y. (where $1 \le j \le y$)

q = 0.5

4. The degree of GRC of each alternative from I^{+ve} and I^{-ve} is computed as follows:

$$C_1^{+ve} = \sum_{j=1}^{y} W_j C_{ij}^{+ve}, i = 1,2, \dots x$$

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$$C_1^{-ve} = \sum_{j=1}^{y} W_j C_{ij}^{-ve}, i = 1,2, \dots x$$

5. The following objective optimization models (Z) are taken into in order to obtain the whole weight information:

$$(\text{Z-1})\left\{\begin{array}{c} minC_i^{-ve} = \sum_{j=1}^{y} W_j C_{ij}^{-ve}, i = 1,2, \dots x \\ maxC_i^{+ve} = \sum_{j=1}^{y} W_j C_{ij}^{+ve}, i = 1,2, \dots x \\ subject\ to : C \in S \end{array}\right\} \quad (10)$$

6. The single objective optimization model is comprised of the sum of the aforementioned multiple objective optimization models, each given an equal weight:

$$(\text{M-2}) \left\{\begin{array}{c} minC = \sum_{i=1}^{x} \sum_{j=1}^{y} (C_{ij}^{-ve} - C_{ij}^{+ve}) w_j \\ subject\ to : C \in S \end{array}\right\} \quad (11)$$

The best solution w is achieved as the attribute weight vector by solving the model (M – 2) for it.

7. The following equation provides each possibility from I^{+ve}'s relative GRD:

$$C_i = \frac{C_i^{+ve}}{C_i^{-ve} + C_i^{+ve}}, i = 1,2, \dots x \quad (12)$$

8. After ranking all the alternatives, the sensor nodes with maximum coverage, residual energy and buffer size are selected as DCPs for collecting data from a set of neighboring sensors.
9. MDC Selection Process

The steps involved in this process are as follows:

- Using a timer (T), each node competes for the DCP nomination.
- The following equation is used by each node to calculate its timer value.

$$T(n_i) = \{(a*CP(n_i))+(b*V(n_i))+(c+E_{res}(n_i))\} \quad (13)$$

Where a+b+c = 1

IV. SIMULATION RESULTS

4.1 Simulation Parameters

The proposed Fuzzy-GRA method is implemented in NS3. The number of nodes are kept as 100 whereas the speed of MDC ranges from 20m/s to 40m/s and its range varies from 250m to 450m. The transmission rate is 50Kb and traffic model is Constant Bit Rate (CBR).

4.2 Comparison Results

The performance of Fuzzy-GRA method is compared with Data Collection Maximization Problems with Hovering Coverage Overlapping (DCMP-HCO) [13], in terms of data collection delay, packet delivery ratio (PDR) and average residual energy (ARE) metrics. The MDC moving range is varied as from 250m to 450m.

The comparison results are presented in this section.

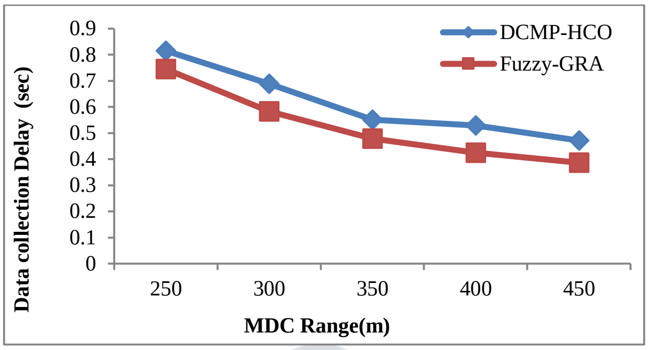

Figure 1. Range Vs Data Collection Delay

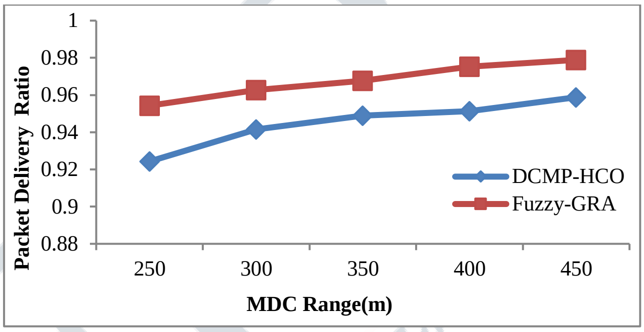

Figure 2. Range Vs PDR

From figure 1, we can observe that the Data Collection delay of Fuzzy-GRA is 15% lesser than DCMP-HCO. Figure 2 shows that PDR of Fuzzy-GRA is 2% higher than DCMP-HCO.

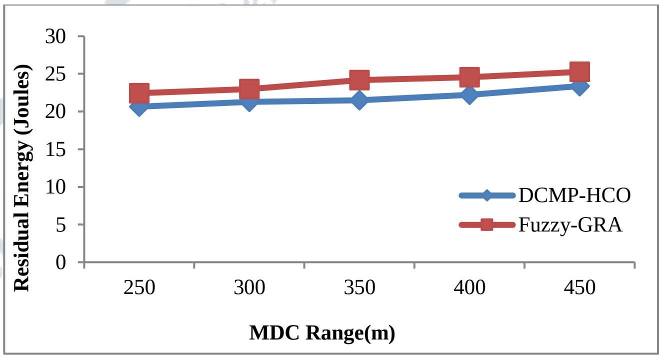

Figure 3. Range Vs ARE

From figure 3, we can observe that ARE of Fuzzy-GRA is 9% higher than DCMP-HCO.

V. CONCLUSION

In this paper, a Fuzzy-GRA based Estimation technique of DCP for MDC in IoT-WSN is proposed. In this technique, the Fuzzy-GRA (grey relational analysis) method is used for selecting the data collection points (DCPs) with maximum coverage, residual energy and buffer size. The performance of Fuzzy-GRA method is compared with DCMP-HCO technique in terms of data collection delay, PDR and ARE metrics. By simulation results, it has been shown that the Fuzzy-GRA attains maximum PDR and ARE with reduced data collection delay.

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