



## COPRAS BASED CLUSTERING STRATEGY TOWARD ENERGY-EFFICIENT IOT-CLOUD TRANSMISSION

Arpita Biswas<sup>1</sup>, Abhishek Majumdar<sup>2</sup>, K. L. Baishnab<sup>3</sup>

<sup>1</sup>Ph.D Scholar, Department of Electronics and Communication Engineering,  
NIT Silchar, Silchar, Assam, India.

<sup>2</sup>Assistant Professor, Department of Computer Science and Engineering,  
Karunya Institute of Technology and Sciences, Coimbatore, India

<sup>3</sup>Associate Professor and Head, Department of Electronics and  
Communication Engineering, NIT Silchar, Silchar, Assam, India.

<sup>1</sup>arpita.nits@ieee.org, <sup>2</sup>abhishek@karunya.edu, <sup>3</sup>klbaishnab@gmail.com

Corresponding Author: Dr. Abhishek Majumdar

<https://doi.org/10.26782/jmcms.2020.07.00006>

### Abstract

*IoT is a globally accepted smart technology that has the ability to connect each and almost every physical devices through the network. It acts as a bridge between cloud environment and physical environment. It is mainly used to connect the hardware devices like sensors, actuators, storage, hardware, and software to acquire or exchange data. These devices collect the information from the physical world and convert this into useful information that can help in decision making. Since IoT connects everything to the network, so it may face the problem of a large amount of energy loss. In this respect, this paper mainly focuses on reducing the energy loss problem and designing of an energy efficient data transfer scenario between cloud and IoT devices. For this reason, a Complex Proportional Assessment (COPRAS) based clustering approach has been proposed in this work to select the cluster premier effectively and form the set of best clusters for maximizing the network lifetime. The proposed work deals with data transmission model between IoT and cloud that confirms the improvement in energy efficiency, network lifetime, and latency. Furthermore, the sensitivity analysis has also been carried out and satisfactory results has been obtained.*

**Keywords :** Cloud Computing, IoT, MCDM, Clustering

### I. Introduction

The entire world is currently experiencing an exceptional increase in IoT implementation and solutions. IoT guides the modern world becoming smarter gradually through diverse application areas such as intelligent healthcare services,

*Copyright reserved © J. Mech. Cont. & Math. Sci.  
Arpita Biswas et al*

smart agriculture, smart energy grids, home and building automation, traffic control, etc. [I-IV, XXIX]. IoT can connect several devices or equipment through the internet to aggregate data, make important decisions and other desired activities.

In IoT architecture, devices configured for collection of data from various sources are mostly using battery-driven energy. Besides, every device exhausts some amount of energy at the transmission time that can also compromise the network lifetime to an extent. Moreover, the failure of the IoT device can result in a critical data loss. Hence, it is necessary to maintain the relationship between data transmission and battery energy for prolonging the network lifetime. In the present scenario, IoT devices have been deployed in different regions and responsible for acquiring intended data from various sources. After that, every device sends data to the data-analytic-center (DAC) which in turn send it to the cloud server for further storage or in-depth analysis. But during this process, every transmission from every device to DAC consumes an unfavorable amount energy. Besides this, if every device sends data to the data analytic center then it will consume more energy and it will be a critical task for the DAC to control the data flow. The calculation of energy consumption of IoT devices can be made by energy models [XXIV], [XXV]. In this regard, clustering of devices into distinct clusters can be a proficient way to improve the energy efficiency of the network. Every device in the cluster acquire data and transmit it to their respective cluster premier which in turn aggregate the data and transmit to the Data Analytics Center.

This paper has been concerned with an efficient cluster premier selection followed by an effective cluster formation procedure that confirms IoT battery energy saving and enhanced network lifetime. In this paper, a proposed Complex Proportional Assessment (COPRAS) based clustering approach has been followed to get the desired set of cluster premiers having better fitness values which can form a suitable set of a cluster of devices that confirms a better energy efficient network. For all this evaluation, several criteria's have been considered such as residual energy, distance goodness ratio over DAC, the average distance between devices and sleep time.

The rest of the paper has been organized as follows: Section II highlights the literature review of the relevant field in detail. Methodology of the concerned area has been described in Section III. Section IV represents the experimentation and results analysis. Finally, the paper has been concluded in Section V.

## **II. Literature Review**

In 2020, T. Ayesha et al. [XXII] designed a Priority based energy efficient routing protocol for IoT network (lower power and lossy network). This technique increases the robustness and ultimately prevents congestion of the network. The proposed method reduces the energy consumption, network overhead and end to end delay and also better than the QRPL routing method of IoT network. In 2019, Majumdar et al. [III] proposed a HWPSO-based clustering approach for ensuring an edge device configured energy efficient e-Healthcare network. Authors considered the randomly deployed micro data centers as the edge devices. They considered

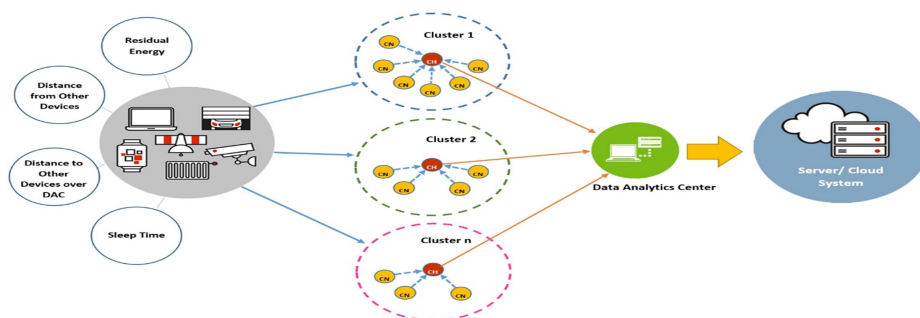
energy, distance and computational load factors of the edge devices for generating fitness function. Kwon et al. [IX] proposed variable categorized clustering algorithm (VCCA) using fuzzy logic and applied it for the selection of cluster head in IoT local network. The VCCA uses fuzzy inference system (FIS) to select CH with lower complexity and to attain higher scalability among cluster variables by applying the rule based variable. Authors claimed that the proposed algorithm outperformed other algorithms with respect to various network performance factors including energy conservation, latency, throughput, and network lifetime. Whereas, Reddy and Babu [XIV], [XV] also proposed a technique for clustering and cluster heads selection in IoT device network to transmit data to the base station. For cluster head selection, a hybrid gravitational search algorithm (GSA) with artificial bee colony (ABC) optimization approach was used. Considering the stopping criteria, the GSA algorithm performed the update of the position and velocity of the agents. Subsequently, the GSA algorithm followed the updating procedure of employed bee phase of the ABC algorithm for updating the velocity. The distance, energy, delay, load, and temperature of the IoT devices was considered as the parameters for the cluster head selection process. In 2017, Dhumane et al. proposed an energy efficient routing algorithm named Fractional Gravitational Grey Wolf Optimization (FGGWO) for multipath data transmission [V]. This algorithm modified the Grey Wolf Optimization by integrating FGSA in it. Basically, the work was inspired by the Ant Colony Optimization (ACO) algorithm that discovered multipath based n clustering technique. Their proposed algorithm improve the routing process of ACO in two ways. Firstly, Fractional Gravitational Search Algorithm (FGSA) is used for the selection of cluster heads and later then FGGWO is utilized for the generation of multiple paths between source and destination. Parameters such as, energy, inter and intra-cluster distance, delay and lifetime are considered for the generation of fitness function which in turn provides the desired optimal paths for the transmission. Van et al. [XVII] proposed a fuzzy inference system based clustering protocol considering current position and the residual energy as the parameters. Dhumane et al. also presented an optimal IoT routing strategy using k-means clustering algorithm and Genetic Algorithm. The K-means clustering algorithm was used for the selection of best cluster head and cluster formation whereas the Genetic Algorithm (GA) was used for the selection of optimal path. The GA was based on the energy cost of the cluster head, the level of the sensor node and length of the path. Authors asserted that the resultant path obtained by GA can have more reliability, higher speed and lifetime [VI]. In 2017, Kaur et al. [XVIII] proposed three layers based energy-efficient technique for IoT. The first layer was configured with hardware element and used to collect a large amount of information from the environment and to send them for data analysis. This layer was responsible for the calculation of the sleep interval of devices based on remaining battery level, their previous usage history, and quality of information for a particular application. The second layer was responsible for storing, processing and analyzing data to extract useful information. The third layer was responsible for providing the desired service to the end user. In 2016, Song et al. [XIII] propounds a novel quantum particle swarm optimization (QPSO) scheme for cluster heads selection. In 2017, Yaqoob et al. [VIII] deeply illustrated the

architecture, taxonomies and recent studies on IoT. In addition, they highlighted the future challenges and requirements in IoT architecture in detail. In 2017, M. K. Reddy et al. [XIV] also presented an energy thrifty cluster head selection and clustering protocols under wireless sensor network (WSN)-based IoT. A self-adaptive whale optimization algorithm (SAWOA) was suggested and followed to achieve the intended results and prolonging the network lifetime. During simulation they considered both load and temperature of IoT devices along with the basic parameters such as energy, distance, and delay of sensor nodes. The fitness function was designed such that the effective network performance can be obtained if the preserved energy is high and delay, distance, load, and temperature are less. The suggested SAWOA differs from the standard WOA algorithm in respect to the position update function where the value of random variable  $k$  which confirm the selection of either spiral encircling mechanism or spiral updating position is determined by evaluating the fitness of previous and current iteration. The same group of authors [XVI] also performed similar work and suggested to use the combination of two evolutionary algorithms namely Optimal Secured Energy Aware Protocol (OSEAP) and Improved Bacterial Foraging Optimization (IBFO) algorithm to accomplish the desired tasks of energy-aware routing. In this work, firstly the Fuzzy C-Means (FCM) is used to make clusters of all sensors. Subsequently, OSEAP is utilized to manage the energy consumption of the cluster head. Then the group key distribution procedure is utilized for transmitting a message from source to destination node through the selected path. If any packet drop or attack occurred in the node then this key gets changed and another path will be selected for transmission. In 2017, Martins et al. [X] proposed GA based optimized clustering strategy for constrained networks by considering Internet Engineering Task Force (IETF) Constrained RESTful Environments (CoRE) standards for data transmission and CoRE interfaces. Authors observed an improved battery level at the nodes, transmission energy and node processing capability. As CoRE Interfaces uses fewer control messages during the communication process thus energy consumption can be reduced. In 2016, Akgul et al. [XIX] designed an approach for optimizing the energy consumption with coverage area for IoT devices. Additionally a concept of smart and self-configured sensors which has the capability of putting itself into sleep mode and active mode based on requirement was also suggested. In 2015, Rani et al. [XX] suggested a novel scheme for energy efficient data transmission in IoT by designing a hierarchical network, a model for energy efficient IoT and a minimum energy consumption transmission algorithm. In 2015, Da Silva et al. [VII] proposed an energy efficient strategy wherein the précised level of transmission power of each participating node was evaluated using PSO without making disconnected areas in the sensor cluster and keeping the cluster fully-connected. Authors claimed that their approach can able to save almost 1dBm power. However this approach had been tested for different scenarios but found not convergent for all, thus need further investigation. In 2013, Liang et al. [XI] described the concept of sleep interval of IoT devices. Moreover, they proposed a strategy to maximize the sleep interval for energy saving. In 2014, Zhou et al. [XXIII] proposed a tree-based architecture for saving the energy of the diversely distributed sensor nodes. They built a tree structure of sensor nodes and used it for data

transmission in an energy efficient way. Similarly, in 2014, J. Tang et al. [XII] also considered a tree architecture for data transmission on IoT. In 2005, Muruganathan et al. [XXI] suggested an idea about centralized routing protocol where a high-energy base station was responsible for distributing the energy consumption evenly to sensor nodes that confirms an improved network lifetime. Recently, Majumdar et al. [XXVIII] also suggested an energy efficient e-Healthcare framework using a novel HEO- $\mu$ GA algorithm technique and found satisfactory results.

### III. Methodology

In this paper, a well-organized framework has been proposed for energy efficient data transmission between IoT and cloud environment. Figure 1 represents the proposed energy efficient clustering framework. In the proposed framework, IoT devices have been scattered into different places and responsible for continuously monitoring of the surroundings. But rather than collecting data in every second and sending them to the DAC, the devices make clusters and send data to the particular device leader called 'cluster premier (CP)'. The desired set of devices with higher fitness values will be selected as CP. If every device sends data directly to the DAC each time then the process may consume a large amount of energy and also becomes very messy that will be hard to manage. But a considerable amount of energy can be saved if the devices make energy efficient clusters among themselves and send data to the CP which in turn send data to the DAC periodically. For that, four relevant energy related criteria of IoT devices namely residual energy, Average sleep time, Average distance to other devices over DAC, Average distance from other devices have been considered for the selection of CP as well as the best set of cluster formation. This approach reduces the energy consumption of IoT devices and improve the network lifetime and latency. Since the IoT devices can be movable so it can be possible that a CP at the present time may not be the best one after a certain time interval. As a result, the set of clusters may also be changed accordingly after every round of data transmission due to the continuous change in criteria values of each device. Each criteria of each device will be calculated repeatedly using a multi criteria decision making process to find the best set of CP at each round and based on that the best cluster set will be formed.



**Fig. 1:** Proposed IoT-Cloud data transmission framework

### **COPRAS-Based Clustering**

In this paper, after rigorous surveying of different multi-criteria decision-making process, energy model, clustering techniques, a novel COPRAS based clustering approach has been proposed that suits for the proposed framework and for energy efficient data transmission between IoT and cloud environment. For the selection purpose of CP, COPRAS, a multi criteria decision method has been used along with the Analytical Hierarchy Process (AHP) for criteria weight determination. Moreover, a fitness function has also been prepared with the set of relevant criteria for the evaluation of each node. Considering this, a proposed clustering algorithm has been followed for the suitable set of cluster formation.

In this work, the fitness function consists of following four parameters or criteria:

Residual energy:

$$RE_i \Big|_{1 \leq i \leq m} = \frac{E_i}{E_0} \Big|_{1 \leq i \leq m} \quad (1)$$

where  $E_i$  = current energy level of  $i^{\text{th}}$  device at time 't'.

Average sleep time:

$$ST = \frac{\sum_{i=1}^s T_i}{s} \quad (2)$$

where  $T_i$  = sleep interval (in seconds) for  $i^{\text{th}}$  time interval of a device;  $s$  = total number of sleep intervals recorded for a device;

Average distance to other devices over DAC:

$$Dist_{dac} = \frac{\sum_{j \neq i; n_j \in m}^m d(n_i, n_j)}{\sum_{j \neq i; n_j \in m}^m d(n_j, DAC)} \quad (3)$$

where

$$d(n_i, dac) \Big|_{1 \leq i \leq m} = \sqrt{(dac(x) - n_i(x))^2 + (dac(y) - n_i(y))^2} \quad (4)$$

Average distance from other devices:

$$Dist_{oth} = \frac{\sum_{j \neq i; n_j \in m}^m d(n_i, n_j)}{m-1} \quad (5)$$

### **Calculation of Criteria Weights**

In this step, the weights of each criterion has been calculated. Since the most concerning aim is the energy efficiency of IoT device, thus the residual energy criteria is the most important factor among all. The average distance to other devices over DAC and the average distance from other devices have been considered as the two most significant parameters in the proposed network because they save

transmission time and network bandwidth. The average sleeping time has also been considered as an in IoT network since higher sleep time will save the energy indirectly.

The pairwise comparison matrix is now generated as shown in Table 2 by utilizing the Saaty’s significance scale [III] listed in Table 1. Table 3 represents the weights of each criterion which has been calculated using the analytic hierarchy process (AHP) method. The obtained consistency ratio is  $CR = CI/RI$  (i.e.  $0.0733 < 0.1$ ). Therefore, the weights are consistent and can be used in further processing.

**Fitness Function Derivation**

In this step, the fitness value calculation of each device according to the proposed novel fitness function has been conducted to form the suitable clusters. Considering each criteria (Eqn. (1-5)) and their respective weights the fitness function has been formulated as shown in Eqn. (6).

$$Fitness = W_1RE + W_2(1 - Dist_{dac}) + W_3(1 - Dist_{oth}) + W_5ST \quad (6)$$

**Final Cluster Formation and Head Selection**

The COPRAS based decision making algorithm along with the AHP has been followed here to rank the devices in a particular location on the basis of their current performance statistics at a certain timestamp. The top best devices will be chosen as cluster premiers (CP). Algorithm 1 stated the steps involved in CP selection. Using these CP as the centroids, different clusters will be formed by following the Algorithm 2. In case of clustering, the two most promising cluster sets will be taken into consideration each time and the best one with highest cluster fitness value will be chosen as the desired cluster set for that time being. In this way, the best cluster set with a set of best cluster premiers will be obtained. After the formation of the entire cluster, every device within a cluster will send the acquired or sensed information to their respective cluster premiers.

**Table 1: Significance Scale of Criteria [III]**

Definition	Intensity of significance
Equally important	1
Moderately more important	3
Strongly more important	5
Very strongly more important	7
Extremely more important	9
Intermediate	2,4,6,8



**Table 2: Pairwise Comparison Matrix for the Criteria**

Criteria	RE	ST	Dist <sub>dac</sub>	Dist <sub>oth</sub>
RE	1	3	3	5
ST	0.33	1	3	5
Dist <sub>dac</sub>	0.33	0.33	1	3
Dist <sub>oth</sub>	0.20	0.20	0.33	1

**Table 3: Weight Determination of Criteria using AHP**

Criteria	Weights (W)	$\lambda_{max}$ , CI, RI	CR
RE	0.4916	Max. Eigen value $\lambda_{max}=4.198$ CI= 0.066 RI= 0.9	0.0733
ST	0.2911		
Dist <sub>dac</sub>	0.1502		
Dist <sub>oth</sub>	0.0670		

Furthermore, after gathering all the information for a time interval, the cluster premier, in turn, sends the information to the DAC where a temporary data analysis can be made and further send them to the cloud environment for in-depth analysis.

**Algorithm 1: COPRAS based cluster premier selection**

**Input:** Set of IoT devices  $D = \{n_1, n_2, n_3 \dots n_m\}; 1 \leq m \leq \infty$ ; Criteria set  $C = \{C_1, C_2, C_3 \dots C_p\}; 1 \leq p \leq \infty$ ;

**Output:** A ranked set of IoT devices

Generate and fix the positions of ‘m’ number of IoT devices ( $n_1, n_2 \dots n_m$ ) and DAC (dac).

Initialize weights of each criteria ( $w_i$ ) and initial Energy ( $E_0$ ) of each device.

Calculate different criteria values for each device at time ‘t’.

Formation of decision matrix:

$$M_{i,j} \left| \begin{matrix} 1 \leq i \leq m \\ 1 \leq j \leq p \end{matrix} \right. = C_j(n_i) \left| \begin{matrix} 1 \leq i \leq m \\ 1 \leq j \leq p \end{matrix} \right. \quad (7)$$

Normalization of decision matrix;



The original sequence for the Higher-the-Better (HB) criterion is normalized as:

$$M_{i,j}^{norm} \Big|_{\substack{1 \leq i \leq m \\ 1 \leq j \leq p}} = \frac{M_{i,j} - \min(M_j)}{\max(M_j) - \min(M_j)} \quad (8)$$

Meanwhile, the original sequence for the Lower-the-Better (LB) criterion is normalized as:

$$M_{i,j}^{norm} \Big|_{\substack{1 \leq i \leq m \\ 1 \leq j \leq p}} = \frac{\max(M_j) - M_{i,j}}{\max(M_j) - \min(M_j)} \quad (9)$$

where  $\max M_j$  is the highest value of  $M_{ij}$  for the  $j^{\text{th}}$  criteria;  $\min M_j$  is the lowest value of  $M_{ij}$  for the  $j^{\text{th}}$  criteria; and  $M_{i,j}^{norm}$  is the normalised data.

Calculation of weighted normalized decision matrix;

$$M_{i,j}^{w,norm} \Big|_{\substack{1 \leq i \leq m \\ 1 \leq j \leq p}} = M_{i,j}^{norm} \Big|_{\substack{1 \leq i \leq m \\ 1 \leq j \leq p}} \times w_j \quad (10)$$

Sum of HB criteria and LB criteria of each device;

$$HB_i \Big|_{1 \leq i \leq m} = \sum M_{i,j}^{w,norm} \Big|_{\substack{1 \leq i \leq m \\ 1 \leq j \leq hb\_p}} \quad (11)$$

where  $hb\_p$  specifies the HB criteria.

$$LB_i \Big|_{1 \leq i \leq m} = \sum M_{i,j}^{w,norm} \Big|_{\substack{1 \leq i \leq m \\ 1 \leq j \leq lb\_p}} \quad (12)$$

where  $lb\_p$  specifies the LB criteria.

Determination of the relative significance value of devices;

$$RS_i \Big|_{1 \leq i \leq m} = HB_i + \frac{\min(LB) * \sum_{j=1}^m LB_j}{LB_i * \sum_{j=1}^m \frac{\min(LB)}{LB_j}} \quad (13)$$

Calculation of quantitative utility;

$$Q_i \Big|_{1 \leq i \leq m} = \frac{RS_i}{\max(RS)} \quad (14)$$

Ranking order of devices will be made by following the principle –‘higher the  $Q_i$  higher the rank’.

The desired set of best devices will be chosen as cluster premier.

End.

### Algorithm 2: Cluster Formation

**Input:** Set of IoT devices  $D = \{n_1, n_2, n_3 \dots n_m\}$ ;  $1 \leq m \leq \infty$ ; Set of cluster premiers  $CP = \{cp_1, cp_2, cp_3 \dots cp_k\}$ ;  $1 \leq k \leq \infty$ ;

**Output:** Formation of suitable set of clusters

Assume a set of clusters  $(Cl_1, Cl_2, \dots, Cl_k)$  with each  $cp_i$  appointed as their cluster premiers.

Compute the distance of all devices from each 'cp';

$$d(n_i, cp_j) \Big|_{\substack{1 \leq i \leq m \\ 1 \leq j \leq k}} = \sqrt{(cp_j(x) - n_i(x))^2 + (cp_j(y) - n_i(y))^2} \quad (15)$$

Keep record of least two distances  $d(n_i, cp_j)$  for every  $i^{\text{th}}$  device and move that device under two respective clusters  $Cl_j$  and form two favorable cases namely *case1* and *case2*.

$$n_i \rightarrow \begin{cases} \text{case1}(Cl_j) \\ \text{case2}(Cl_l) \end{cases} \Big|_{\substack{1 \leq j, l \leq k \\ j \neq l \\ d(n_i, cp_j) < d(n_i, cp_l)}} \quad (16)$$

Compute fitness of each cluster under both cases;

$$Fitness(Cl)_{(i,j)} \Big|_{\substack{1 \leq i \leq k \\ 1 \leq j \leq 2}} = \sum \frac{fitness(n_p)_{(i,j)} \Big|_{\substack{1 \leq i \leq k \\ 1 \leq j \leq 2}}}{|Cl_i|} \quad (17)$$

where  $|Cl_i|$ : Number of members under  $i^{\text{th}}$  cluster and  $\forall n_p \in Cl_i$

Find the best case for cluster combination,

If  $Fitness(Cl)_{(i,1)} > Fitness(Cl)_{(i,2)}$  then

Accept 'case1'

Else

Accept 'case2'

End if

End.

#### IV. Simulation and Result Analysis

Thorough simulations have been performed on the proposed algorithm using MATLAB R2012b. The simulation parameters has been described in table 4. The energy dissipation rate per transmission by cluster premier and other cluster members have been shown in Eqn. (18) and Eqn. (19) respectively. All the network parameter values used in the simulation has been drawn in Table 3. However, these values can also be changed as per situation demand. Energy loss for cluster premier in each transmission:

$$E_{CP(i)_{loss}} = E_{idle} + E_A + tE_{amp} \quad (18)$$

*Copyright reserved © J. Mech. Cont.& Math. Sci.*  
*Arpita Biswas et al*

Energy loss for cluster members in each transmission:

$$E_{CM(i)_{loss}} = E_{idle} + E_{amp} \} \quad (19)$$

where,

$CP(i) \in C_i$ ;  $t$ =number of nodes in  $i$ th cluster;

$CM(i) \in C_i$

A sensitivity analysis has also been performed to verify the robustness of the ranking and to understand the effect of different criterion weights on the selection of cluster premier. The concept applied for the sensitivity analysis is to interchange two criterion weights with each other while keeping the others constant. Table 5 represents the COPRAS table for ranking of IoT devices. Figure 2 represents a change in the quantitative utility values (Q) of each device with criteria weight manipulation whereas, Fig. 3 specifies the change in rank of a device with the change in criteria weights. The higher value of Q indicates the better device quality. It has been observed that device-40 yields the first rank in most of the cases and device-11 stands at rank 2 whereas device-18 and device-20 possess the last two ranks most of the time under different conditions. The initial deployment of devices has been depicted in Fig. 4 whereas Fig. 5 shows the formed clusters with their corresponding cluster premiers as centroids. The cluster premiers have been shown as the star shaped symbol inside a pentagonal box. Moreover, the changes in the average residual energy of each cluster with respect to the number of data transmission process has been observed. Figure 6 depicts the cluster residual energy in each transmission for the proposed algorithm. It has been noticed that cluster-3 dies first after transmission number 7,188 and cluster-1 transmits data for the long run. Figure 7 shows the clusters and the cluster premier after 7,188<sup>th</sup> round of data transmission.

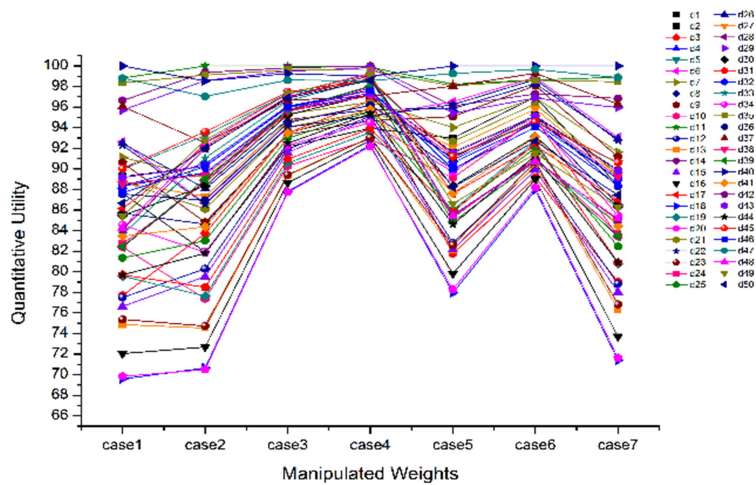
**Table 4: Simulation Parameters [III]**

Properties	Values
Number of devices	50
Number of clusters	5
Initial node energy ( $E_0$ )	3000mAH
Idle state energy ( $E_{idle}$ )	$10^{-4}$ mAH
Data aggregation ( $E_A$ )	$10^{-5}$ mAH/bit
Amplification energy ( $E_{amp}$ )	$10^{-8}$ mAH/bit/m <sup>2</sup>
Packet size from cluster member (k)	20 bit

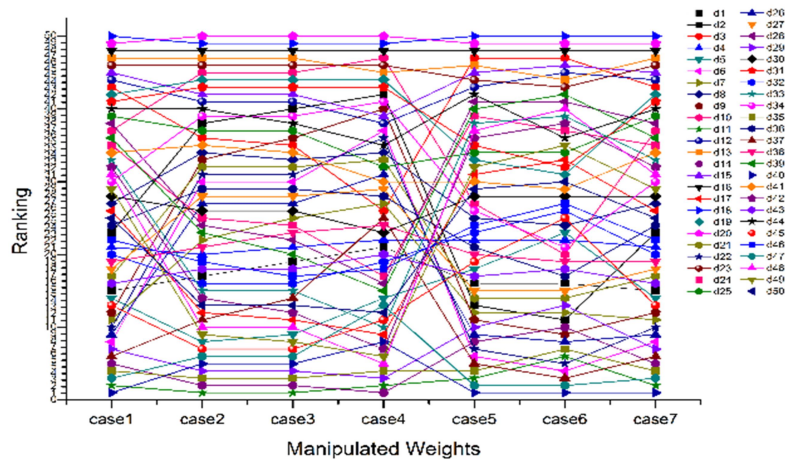
**Table 5: COPRAS Table for Ranking of IoT Devices**

Device Name	Relative Significance Value (RS)	Quantitative Utility (Q)	Rank	Device Name	Relative Significance Value (RS)	Quantitative Utility (Q)	Rank
Device 1	2.11180	89.80508	15	Device 26	2.18942	93.10603	9
Device 2	2.08477	88.65572	22	Device 27	2.10186	89.38238	18
Device 3	1.85092	78.71135	43	Device 28	1.95346	83.07168	38
Device 4	2.09120	88.9292	20	Device 29	2.25130	95.73741	7
Device 5	2.12443	90.34233	14	Device 30	2.02595	86.15431	28
Device 6	2.19470	93.33066	8	Device 31	1.90407	80.9715	40
Device 7	2.15636	91.70038	11	Device 32	2.09030	88.89102	21
Device 8	2.03580	86.57318	27	Device 33	1.98021	84.20919	34
Device 9	2.15011	91.43433	12	Device 34	2.01279	85.59474	30
Device 10	1.96905	83.73483	35	Device 35	2.31280	98.35277	4
Device 11	2.32253	98.76669	3	Device 36	2.07647	88.30306	23
Device 12	1.85049	78.69319	44	Device 37	2.26737	96.42096	6
Device 13	1.79670	76.40559	47	Device 38	2.09598	89.13247	19
Device 14	2.27229	96.63016	5	Device 39	1.95480	83.12877	37
Device 15	1.83139	77.88082	45	Device 40	2.35153	100	1

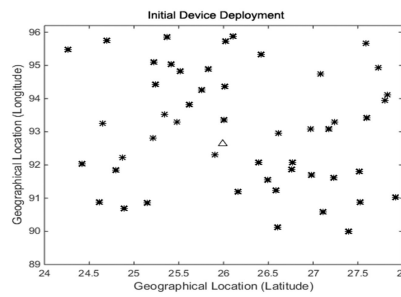
Device 16	1.73328	73.70851	48	Device 41	1.98402	84.37139	33
Device 17	2.03665	86.60970	26	Device 42	1.98932	84.59674	32
Device 18	1.67867	71.38619	50	Device 43	2.10942	89.70415	16
Device 19	1.90231	80.89677	41	Device 44	1.89990	80.79424	42
Device 20	1.68457	71.63699	49	Device 45	2.12557	90.39102	13
Device 21	2.10602	89.55951	17	Device 46	2.07524	88.25040	24
Device 22	2.18751	93.02486	10	Device 47	2.32542	98.88972	2
Device 23	1.80822	76.89555	46	Device 48	1.99156	84.69203	31
Device 24	1.96135	83.40739	36	Device 49	2.01890	85.85487	29
Device 25	1.93683	82.36476	39	Device 50	2.04912	87.13996	25



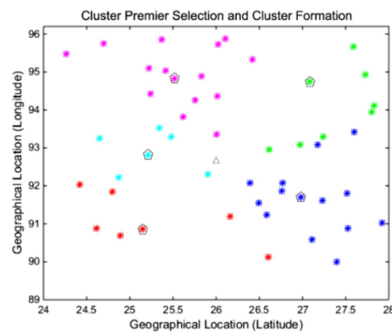
**Fig. 2:** Sensitivity Analysis



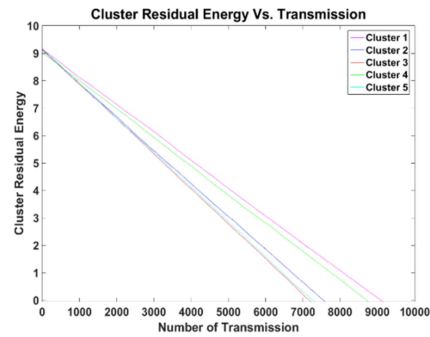
**Fig. 3:** Changes in Rank During Sensitivity Analysis



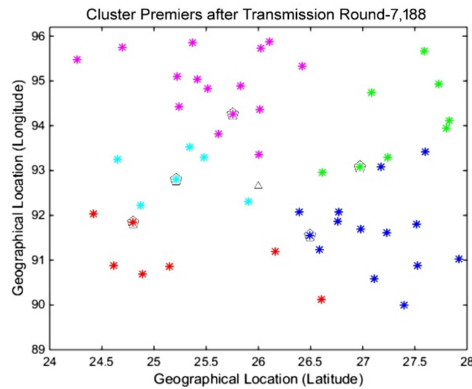
**Fig. 4:** Initial Deployment of Devices



**Fig. 5:** Initial Cluster and Cluster Premier Positions



**Fig. 6:** Clusters residual energy in each transmission



**Fig. 7:** Position of newly formed clusters and cluster premier positions after 7, 188<sup>th</sup> round of data transmission

## V. Conclusion

In this paper, a comprehensive framework for an improved IoT-Cloud transmission framework has been proposed. Moreover, the proposed COPRAS-based clustering algorithm provides a new perspective to form the energy-efficient IoT device cluster set due to its lightweight nature. Besides, the intended fitness function also claims that the lifetime of a network should not be estimated only based on the energy on the devices, but also other critical distance-related parameters and computational status should also be considered. This methodology also endorses the creation of an efficient IoT network where the set of IoT devices configured clusters will about to be equally fit in every respect. Consequently, it will also confirm an optimized energy consumption with better IoT network lifetime. Future work will include the development of a novel and robust optimization based clustering algorithm with a better convergence rate and less computational time.

## VI. Acknowledgement

This publication is an outcome of the R&D work undertaken project under the Visvesvaraya Ph.D. Scheme of Ministry of Electronics & Information Technology, Government of India, being implemented by Digital India Corporation.

## Compliance with Ethical Standards

Conflict of Interest: The authors have no conflict of interests to declare.

**Ethical Approval:** This article does not contain any studies with human participants or animals performed by any of the authors.



## References

- I. A. Majumdar, T. Debnath, S. K. Sood, K. L. Baishnab, “Kysanur forest disease classification framework using novel extremal optimization tuned neural network in fog computing environment”, *Journal of medical systems*, Springer, vol. 42, no.10, pp.187, 2018.
- II. A. Majumdar, A., Biswas, K. L. Baishnab, S. K. Sood, “DNA Based Cloud Storage Security Framework Using Fuzzy Decision Making Technique”, *KSII Transactions on Internet & Information Systems*, vol.13, no.7, pp. 3794-3820, 2019.
- III. A. Majumdar, N. M. Laskar, A. Biswas, S. K. Sood, K. L. Baishnab, “Energy efficient e-healthcare framework using HWPSO-based clustering approach”, *Journal of Intelligent & Fuzzy Systems*, IOS Press, vol. 36, no. 5, pp. 3957-3969, 2019.
- IV. A. Biswas, A. Majumdar, S. Nath, A. Dutta, K. L. Baishnab, “LRBC: a lightweight block cipher design for resource constrained IoT devices”, *Journal of Ambient Intelligence and Humanized Computing*, Springer pp.1-15, 2020.
- V. A. V. Dhumane and R. S. Prasad, “Fractional Gravitational Grey Wolf Optimization to Multi-Path Data Transmission in IoT”, *Wireless Personal Communications*, Springer, vol. 102, no. 1, pp. 411-36, 2018.
- VI. A. V. Dhumane, R. S. Prasad, and J. R. Prasad, “An optimal routing algorithm for internet of thing enabling technologies”, *International Journal of Rough Sets and Data Analysis (IJRSDA)*, vol. 4, no. 3, pp. 1-16, 2017.
- VII. A. Orsino, G. Araniti, L. Militano, J. Alonso-Zarate, A. Molinaro, A. Iera, “Energy efficient IoT data collection in smart cities exploiting D2D communications”, *Sensors*, vol. 16, no. 6, p.836, 2016.
- VIII. D. Wei, S. Kaplan, H.A. Chan, “Energy efficient clustering algorithms for wireless sensor networks”, In *Communications Workshops*, 2008. *ICC Workshops' 08. IEEE International Conference on*, pp. 236-240, 2008.
- IX. G. L. da Silva Fré, J. de Carvalho Silva, F.A. Reis, and L.D.P. Mendes, “Particle Swarm optimization implementation for minimal transmission power providing a fully-connected cluster for the internet of things,” in *International Workshop on Telecommunications (IWT)*, pp. 1–7, 2015.
- X. I. Yaqoob, E. Ahmed, I.A.T. Hashem, A.I.A. Ahmed, A. Gani, M. Imran, M. Guizani, “Internet of things architecture: Recent advances, taxonomy, requirements, and open challenges”, *IEEE wireless communications*, vol. 24, no. 3, pp.10-16, 2017.

- XI. J. H. Kwon, M. Cha, S. B. Lee, and E. J. Kim, "Variable-categorized clustering algorithm using fuzzy logic for Internet of things local networks", *Multimedia Tools and Applications*, Springer, vol. 78, no.3, pp. 2963-82, 2019.
- XII. J. A. Martins, A. Mazayev, N. Correia, G. Schütz, and A. Barradas, "GACN: Self-clustering genetic algorithm for constrained networks", *IEEE Communications Letters*, vol. 21, no. 3, pp. 628-31, 2017.
- XIII. J.M. Liang, J.J. Chen, H.H. Cheng, Y.C. Tseng, "An energy-efficient sleep scheduling with qos consideration in 3gpp lte-advanced networks for internet of things," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems*, vol. 3, no. 1, pp.13-22, 2013.
- XIV. J. Tang, Z. Zhou, J. Niu, Q. Wang, "An energy efficient hierarchical clustering index tree for facilitating time-correlated region queries in the Internet of Things", *Journal of Network and Computer Applications*, vol. 40, pp.1-11, 2014.
- XV. L. Song, K. K. Chai, Y. Chen, J. Loo, S. Jimaa, and J. Schormans, "QPSO-based energy-aware clustering scheme in the capillary networks for Internet of Things systems", in *Wireless Communications and Networking Conference*, IEEE, April 2016, pp. 1-6.
- XVI. L. Song, K.K. Chai, Y. Chen, J. Schormans, J. Loo, A. Vinel, "QoS-Aware Energy-Efficient Cooperative Scheme for Cluster-Based IoT Systems", *IEEE Systems Journal*, vol. 11, no. 3, pp.1447-1455, 2017.
- XVII. M. P. K. Reddy and M. R. Babu, "Implementing self adaptiveness in whale optimization for cluster head selection in Internet of Things", *Cluster Computing*, Springer, pp. 1-12, 2018.
- XVIII. M. P. K. Reddy and M. R. Babu, "Energy Efficient Cluster Head Selection for Internet of Things", *New Review of Information Networking*, Taylor & Francis, vol. 22, no. 1, pp. 54-70, 2017.
- XIX. M. P. K. Reddy and M. R. Babu, "An Evolutionary Secure Energy Efficient Routing Protocol in Internet of Things", *International Journal of Intelligent Engineering and Systems*, vol. 10, no. 3, pp. 337-46, 2017.
- XX. N. T. Van, T. T. Huynh, and B. An, "An energy efficient protocol based on fuzzy logic to extend network lifetime and increase transmission efficiency in wireless sensor networks", *Journal of Intelligent & Fuzzy Systems*, IOS Press, vol. 35, no. 6, pp. 5845-5852, 2018.
- XXI. N. Kaur, and S.K. Sood, "An Energy-Efficient Architecture for the Internet of Things (IoT)", *IEEE Systems Journal*, vol.11, no.2, pp.796-805, 2017.

- XXII. Ö.U. Akgül, B. Canberk, “Self-Organized Things (SoT): An energy efficient next generation network management,” *Computer Communications*, vol. 74, pp.52-62, 2016.
- XXIII. S. K. Singh, M.P. Singh, D.K. Singh, “Energy-efficient homogeneous clustering algorithm for wireless sensor network”, *International Journal of Wireless & Mobile Networks (IJWMN)*, vol. 2, no. 3, pp.49-61, 2010.
- XXIV. S. Rani, R. Talwar, J. Malhotra, S.H. Ahmed, M. Sarkar, H. Song, “A novel scheme for an energy efficient Internet of Things based on wireless sensor networks”, *Sensors*, vol. 15, no. 11, pp.28603-28626, 2015.
- XXV. S. D. Muruganathan, D. C. Ma, R. I. Bhasin, A. O. Fapojuwo, “A centralized energy-efficient routing protocol for wireless sensor networks”, *IEEE Communications Magazine*, vol. 43, no. 3, pp. S8-13, 2005.
- XXVI. T. Ayesha, S. Sadaf, D. Sinha, and A. K. Das. “Secure Anti-Void Energy-Efficient Routing (SAVEER) Protocol for WSN-Based IoT Network”, In *Advances in Computational Intelligence*, pp. 129-142. Springer, Singapore, 2020.
- XXVII. Z. Zhou, J. Tang, L.J. Zhang, K. Ning, Q. Wang, “EGF-tree: an energy-efficient index tree for facilitating multi-region query aggregation in the internet of things”, *Personal and Ubiquitous computing*, vol.18, no.4, pp.951-966, 2014.
- XXVIII. A. Majumdar, T. Debnath, K. L. Baishnab, S. K. Sood, “An Energy Efficient e-Healthcare Framework Supported by HEO- $\mu$ GA (Hybrid Extremal Optimization Tuned Micro-GeneticAlgorithm)”, *Information System Frontiers*, Springer, 2020, DoI: <https://doi.org/10.1007/s10796020-10016-5>.
- XXIX. A. Majumdar, M. Sharma, “Enhanced information security using DNA cryptographic approach. *International Journal of Innovative Technology and Exploring Engineering*”, vol.4, no.2, pp. 72-76, 2020.