Modified Flower Pollination Algorithm based Resource Management Model for Clustered IoT Network

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Abstract

Internet of Things (IoT) is a technological innovation that defined interaction and computation of latest period. The objects of Internet of Things would empower by embedded gadgets whose limited sources has to be managed effectively. IoT usually means a network of devices connected through wireless network and interacts through internet. Resource management, particularly energy management, becomes a serious problem while devising IoT gadgets. Numerous researchers stated that routing and clustering were energy effectual solutions for optimum resource management in IoT setting. This study introduces a Modified Flower Pollination Algorithm based Resource Management (MFPA-RMM) model for Clustered IoT Environment. The presented MFPA-RMM model majorly focuses on the clustering the IoT devices in such a way that the resources are proficiently managed. The MFPA-RMM model is derived based on the fuzzy c-means (FCM) with FPA. The FPA approach is called heuristic algorithm has benefits of global optimization and faster convergence, therefore it was incorporated to FCM system for resolving the advantages and disadvantages of FCM method termed FCM-FPA mechanism. The result analysis of the MFPA-RMM model reported the enhanced performance of the MFPA-RMM model over other well-known techniques like LEACH and TEEN.

Keywords: Clustering; Internet of Things; Heuristics; Flower pollination algorithm; Resource management

1. Introduction

Internet of Things is a promising ideal models in an ongoing period, portrayed by utilizing smart and self-designing substances like sensors, actuators, and RFIDs, were associated with Internet and trade information by sensing, responding to occasions and connecting with the climate [1]. It epitomizes a dream of blending heterogeneous articles while using Internet as a spine of correspondence to lay out collaboration amongst virtual and physical substances. These consistent collaborations amongst heterogeneous items are making IoT a worldview that empowers omnipresent and inescapable applications [2]. Subsequently, Internet observed an unavoidable shift from interconnected end-client nodes to interconnected actual items making a foundation of smarter articles equipped for instructive correspondence and keen handling. Since countless things associate with the Internet, subsequently, having a sufficient engineering that grants simple availability and control is fundamental. Broad work has been finished in most recent couple of years to track down a general IoT design, yet IoT envelops a

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very extensive variety of utilizations, all things considered, single reference engineering has not been utilized for all substantial executions [3].

An IoT engineering ought to be fit for playing out at least three fundamental capacities viz. aggregation of data and sensing, conveying data and using data to offer types of assistance at the application stage. The data and sensing assortment is finished by actual IoT nodes that sense a few actual boundaries or distinguishes different nodes in smart conditions. The conveyed data can be after used by IoT applications to convey different administrations to the clients [4]. Fig. 1 demonstrates the architecture of clustered IoT.

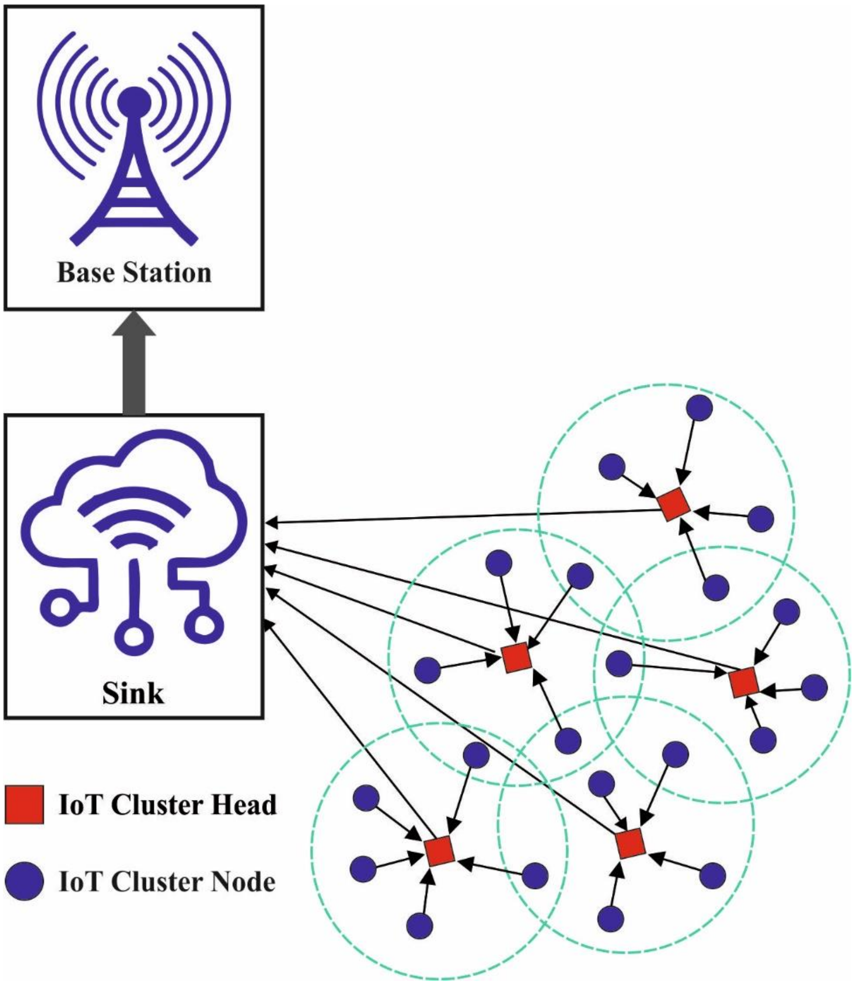

Figure 1: Structure of Clustered IoT Network

IoT assumes an essential part in making present day urban communities successful by associating individuals with worldwide clients [5]. This widespread association helps in the conveyance of legitimate and uncommon data like video, sound, picture, and text. The data trade peculiarity has turned into a huge goal in fostering a smart city. Smart city idea advanced to achieve reasonable and climate amicable urban communities. It has significant systems that utilization key units, for example, IoT, remote sensing, Cloud Computing (CC), big data, etc. Additionally, different defensive sensor networks in particular, Internet of Everything (IoE), Wireless Sensor Networks (WSNs), Web of Things (WoT) Body Sensor Networks (BSN), etc. These systems are locked in successfully in the creation, assortment, implementation and communication of data to upgrade smart city draws near [6]. A bunch of faultless and highly worth data is gotten from smart urban communities utilizing interactive media framework. On the opposite end, media-related sensors, its productivity at top circumstances and unpredictable nature of data assortment procedure animate the requirement for cloud computing (CC) method.

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As per industrial reports, the amount of data created by and gathered from sensor-driven IoT contraptions is set to increment before long than the previous definitely. In this situation, high pinnacle and conflicting data assortment, memory capacity, noticeable transmission of data, and so forth are a portion of the complexities that present danger to CC model. In spite of the advancement of new gadgets and models, it actually stays insufficient the same old style draws near. Just a small bunch of engineers characterized that WSN gather a greatest measure of data [7].

Amongst different parts utilized in smart city advancement, sensor-depended techniques, for example, IoT are anticipated to be the principal answer for handling various difficulties in corporates, schooling, agribusiness, medical services, etc. Extraordinary development in lightweight sensors improved the traditional firms in medical services and business by rejuvenating creative articles and looking for the most extreme consideration of users. Energy effectiveness can be accomplished in geography control by various levelled plan of nodes that outcomes in staying away from energy utilization due to coordinate significant distance correspondences [8]. In such manner, nodes clustering is a significant procedure comparable to a progressive design, which lessens bandwidth misfortune, congestion and IoT network blunder. This is a result of less simultaneous data move between the climate and the base station or sink for a diminished number of nodes. In any case, a proficient numerical demonstrating of group head (CH) determination in IoT isn't productively tended to in that frame of mind of-the-craftsmanship research [9].

Orchestrating provincial nodes as a kind of a group brings about proficient correspondence between nodes in similar bunch and its CH. Then, CHs gather data being sent by the nodes inside a comparing group and frequently pack this data and afterward CHs send the gathered data to the base station or sink. Accordingly, choosing the legitimate CH can altogether lessen energy utilization and increment the lifetime of IoT. Choosing the legitimate CH is pretty much as significant and compelling as the calculation utilized for clustering due to the diminished association traffic in the network and appropriately expanded energy productivity and network lifetime [10].

This study introduces a Modified Flower Pollination Algorithm based Resource Management (MFPA-RMM) model for Clustered IoT Environment. The presented MFPA-RMM model majorly focuses on the clustering the IoT devices in such a way that the resources are proficiently managed. The MFPA-RMM model is derived based on the fuzzy c-means (FCM) with FPA. The FPA approach is called as heuristic algorithm encompassed with the advantages of faster convergence and global optimization, therefore it is incorporated to FCM system for resolving the advantages and disadvantages of FCM method as termed as FCM-FPA mechanism. The result analysis of the MFPA-RMM model reported the enhanced performance of the MFPA-RMM model over other techniques.

The structure of this paper is organized as follow: In Section 2, we discuss the related work. In Section 3 we detail our proposed solution. In Section 4, we evaluate our solution. In Section 5, we conclude our paper and present some perspectives.

2. Related Works

Desai et al. [11] discover an optimum path for effective transmission among the nodes existing in a programmable Industrial IoT (IIoT) system and end user routing algorithm is intended for finding the optimum path for transmission. They incorporate a SDN architecture using IIoT node for construction of a central programmable system and deployed custom routing algorithm for computation. To decrease the transmission delay, the authors integrate Edge Computing Servers (ECS). Jaiswal and Anand [12] developed a Grey wolf optimization-related CH selection methodology for WSN considered various characteristics such as sink distance, energy level of the node, node degree, priority factor, and intra-cluster distance. The study address the routing through QoS attentive relay node collection for consistent and efficient inter-cluster routing from CH to BS.

Dogra et al. [13] developed Tunicate Swarm Algorithm (TSA)-based Optimized Routing Mechanism (TORM) which address the issue of energy-efficacy of SNs for IoT for long sustainability. The motivation behindhand utilizing lately developed TSA optimization technique is its fast convergence and higher exploring ability. The fitness function of TSA employed to TORM, is evaluated by assuming many vital fitness parameter accountable for selecting CH node. Khalid et al. [14] powerfully distribute tasks among the Cloud Networks and the Fog Layers and later optimize allocation of resource in cloud network to guarantee best consumption and rapid responding time of the resource accessible to the end user. They applied a Deadline aware system for migrating the information among cloud and

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Fog network on the basis of data outlining and later applied Service-request predictive and K-Means clustering method for allocating the resource effectively to each request.

Jumnal and SM [15] developed a hierarchical cluster aware technique based on a metaheuristic crow search approach for the optimum selection of host to locate the VM and consolidate a maximal amount of VM on a minimal amount of hosts. The presented technique enhances the energy utilization of datacentre when fulfilling the QoS requirement of application to satisfy SLA. In [16], a cluster-based energy-effective Cognitive IoT (CIoT) is presented that could harvest the radio frequency (RF) energy of primary user (PU) to provide energy utilization of spectrum sensing. A joint optimization problems of node and time is developed for maximizing the spectrum accessing likelihood of the CIoT.

3. The Proposed Model

This study has established a MFPA-RMM model for Clustered IoT Environment. The presented MFPA-RMM model majorly focuses on the clustering the IoT devices in such a way that the resources are proficiently managed. The abiotic, self, biotic and cross-pollination mechanisms are defined in a field optimization and also encouraged by a flower pollination algorithm. The pollination method enclosed a sequence of tedious operation in plant generation principle. A flower and respective pollen gamete tends to offer a consistent solution for the optimization problem [17]. Flower constancy was determined by the correct solution that could be a noticeable one. In the event of local pollination is performed within the smaller area of the exclusive flower was conducted in a shading water.

In another case, global pollination, the pollinator transfers pollen from long distance to higher fitting. Therefore, the 1st and 3rd rules are given by the following equation:

$$x_q^{t+1} = x_p^t + \gamma \times L(\lambda) \times \left(g_* - x_p^t\right) \tag{1}$$

In Eq. (1), x_p^t = pollen vector at t iteration; g_* indicates an existing optimal solution from another existing producing outcomes; $\gamma = $ a indicates the scaling factor to control step size; L indicates pollination strength that is interrelated with a step size of levy distribution. It can be determined by the set of arbitrary calculation that has length of each jump that implies levy likelihood distributed function with huge variant as follows:

$$L \sim \frac{\lambda \times \Gamma(\lambda) \times \sin \frac{\pi\lambda}{2}}{\pi} \times \frac{1}{S^1 + \lambda} S \gg S_0 0, \tag{2}$$

If $\Gamma(\lambda)$ = gamma function. In the event of local pollination, the second and third rules are formulated by:

$$x_p^{t+1} = x_p^t + \varepsilon\left(x_q^t - x_k^{\mathrm{t}}\right) \tag{3}$$

In Eq. (3) x_q^t and x_k^t = 2 pollens from varied flowers from a comparable plants. In arithmetical formation, if x_q^t and x_k^{t} derives from the alike species are preferred from homogeneous population i.e., represented as the local random walk and ε is uniformly distributed random number lies within zero and one. Based on the Flower Pollination Algorithm (FPA) and traditional Fuzzy C-Means (FCM) clustering method, it is given by FCM-FPA methodology for reaching resource provision in fog computation. The primary goal is to employ FPA method in FCM model.

The FCM clustering technique calculates the degree to sampling points come in the clustering using the application of membership function (MF). Consider the clustering sampling set as $X = \{x_1, x_2, x_3 \ldots, x_n\} \subset R^d$, whereby x_p indicates a d dimensional space. There is fundamental prerequisite to classification the sampling set as c. Set the clustering center as $V = \{v_1, v_2, v_3 \ldots, v_c\}$, and define the degree whereby sampling point comes under the j-th classes as μ_{ij}. As well, the fuzzy matrix of sampling space X is $U = (\mu_{ij})$.

The FCM methodology is indicated by succeeding for extrema problems:

$$Q = \min \sum_{p=1}^{n} \sum_{q=1}^{c} \mu_{ij} \text{ objective function } \left\|x_p - v_q\right\|^2 \tag{4}$$

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$$s.t. \sum_{q=1}^{c} \mu_{pq} = 1 , \mu_{pq} \in [0,1],$$

$$q = 1,2, \cdots , n, q = 1,2, \dots , c$$

Here, μ_{pq} indicates the degree belongs to $q\text{-}th$ data points of $p\text{-}th$ clusters, v_q indicates $q\text{-}th$ clusters, $\|x_q - v_q\|$ represents a Euclidean distance from sampling point x_p to a clustering center v_q, and m denotes a fuzzy index. Furthermore, U and V is symbolized by:

$$v_q = \frac{\sum_{p=1}^{n} \mu_{pq}{}^m x_p}{\sum_{p=1}^{n} \mu_{pq}{}^m} \tag{5}$$

$$\mu_{pq} = \frac{1}{\sum_{k=1}^{c} \left(\frac{||x_p - v_q||}{||x_p - v_k||} \right)^{\frac{2}{m\text{-}1}}} \tag{6}$$

This method is called as local optimization methodology for optimum solution via employing hill climbing. The FPA approach is called as heuristic algorithm encompassed through the advantages of faster convergence and global optimization, therefore it is incorporated to FCM system for resolving the advantages and disadvantages of FCM method as termed as FCM-FPA mechanism.

In FCM-FPA model, the primary goal of FCM technique is to calculate the clustering centre, and $x_p = (v_{p1}, v_{p2}, \cdots , v_{pq}, \cdots , v_{pc})$ illustrates a clustering centre set with an individual pollen in FPA, whereby v_{pq} demonstrates $q\text{-}th$ clustering center in $p\text{-}th$ clustering method. Once N represents the population size, it has N clustering methodologies. The fitness levels of each pollen represent the advantage of clustering effects that is selected by the cluster centre. To approximate each pollen, this method exploits the abovementioned FF values:

$$f(x_p) = Q \tag{7}$$

The small Q is, the small the individual pollen fitness whereby cluster effects is effective. According to the FF scores, the local position and global positions are evaluated, location and velocity of each pollen need to be upgraded. With the abovementioned stages, the FCM-FPA method obtain a global approximation outcome. The FCM was carried out for reaching a global optimum solution recurrently. Now, it is employed by the FCM-FPA methodology to complete the fog resource clustering method.

4. Results and Discussion

This section offers a brief analysis of MFPA-RMM method. Table 1 and Fig. 2 provide the average energy consumed (AEC) analysis of the MFPA-RMM model with recent models. The results indicated that the MFPA-RMM model has resulted to reduced AEC over other models. For instance, MFPA-RMM model has obtained AEC of 1 at 300 rounds while the LEACH, TEEN, DEEC, EAUCF, FUCHAR, and EECBRM models have obtained at 112, 119, 125, 177, 229, and 261 rounds respectively. Similarly, with MFPA-RMM model has obtained AEC of 5 at 1430 rounds while the LEACH, TEEN, DEEC, EAUCF, FUCHAR, and EECBRM models have obtained at 442, 565, 526, 700, 1062, and 1327 rounds respectively. At last, with MFPA-RMM model has obtained AEC of 10 at 2354 rounds while the LEACH, TEEN, DEEC, EAUCF, FUCHAR, and EECBRM techniques are obtained at 1301, 1430, 1314, 1547, 2083, and 2122 rounds respectively.

Table 1: AEC of MFPA-RMM Model

	No. of Rounds						
Avg. Energy Consumed	**LEACH**	**TEEN**	**DEEC**	**EAUCF**	**FUCHAR**	**EECBRM**	**MFPA-RMM**
1	112	119	125	177	229	261	300
2	177	248	254	300	377	416	481
3	300	325	313	358	597	603	765
4	364	429	416	487	914	965	1088
5	442	565	526	700	1062	1327	1430

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6	649	894	778	1049	1463	1573	1754
7	901	1062	972	1224	1560	1715	1889
8	1075	1230	1133	1346	1754	1889	2070
9	1191	1392	1237	1443	1934	2064	2258
10	1301	1430	1314	1547	2083	2122	2354

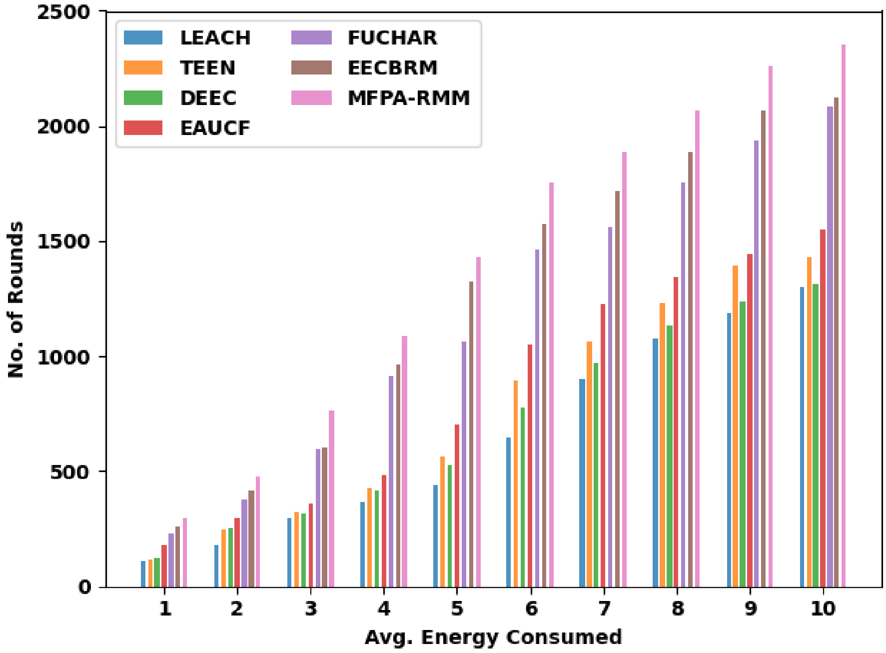

Figure 2: Comparative AEC Inspection of MFPA-RMM Model

Table 2 and Fig. 3 provide the buffer size (BFS) investigation of the MFPA-RMM model with recent models. Based on delay of 1ms, the MFPA-RMM model has offered reduced BFS of 0.0781MB whereas the DSA and baseline models have obtained higher BFS of 0.1788MB and 0.0929MB respectively. Then, based on delay of 5ms, the MFPA-RMM model has offered reduced BFS of 0.0107MB whereas the DSA and baseline models have obtained higher BFS of 0.0341MB and 0.0241MB respectively. Also, based on delay of 10ms, the MFPA-RMM model has offered reduced BFS of 0.0040MB whereas the DSA and baseline models have obtained higher BFS of 0.0184MB and 0.0107MB respectively.

Table 2: BFS Inspection of MFPA-RMM Model

Buffer Size (MB)			
Delay (ms)	**DSA**	**BASELINE**	**MFPA-RMM**
1	0.1788	0.0929	0.0781
2	0.0900	0.0470	0.0298
3	0.0585	0.0346	0.0179
4	0.0437	0.0303	0.0122
5	0.0341	0.0241	0.0107
6	0.0260	0.0193	0.0098
7	0.0255	0.0165	0.0069
8	0.0208	0.0122	0.0064
9	0.0193	0.0122	0.0050
10	0.0184	0.0107	0.0040

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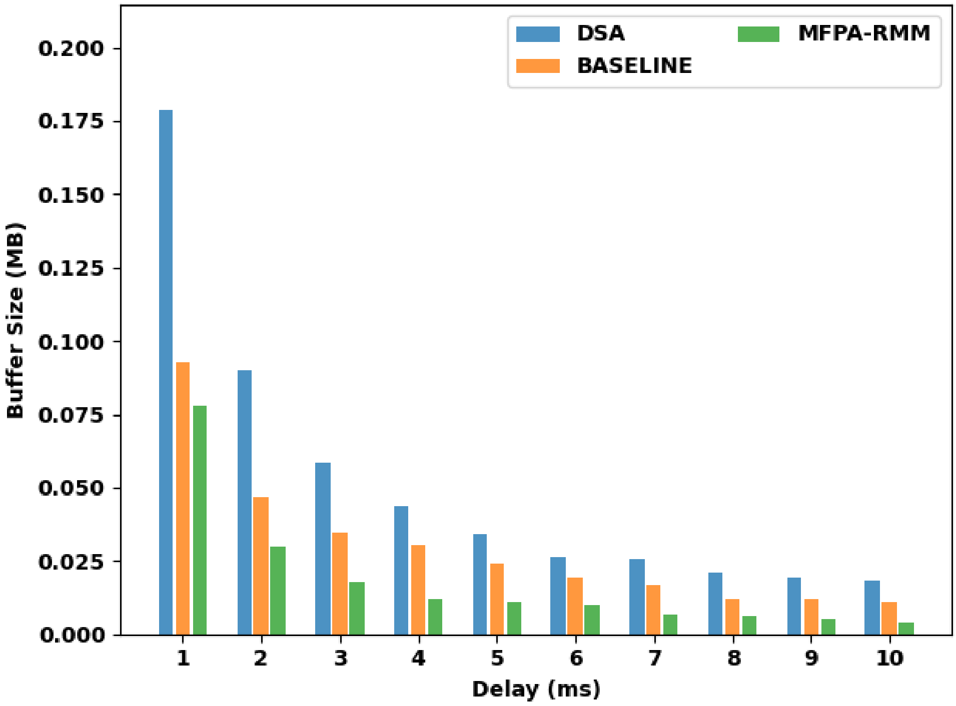

Figure 3: Comparative BFS Inspection of MFPA-RMM Model

Table 3 and Fig. 4 highlight the number of data transmissions (NODT) inspection of the MFPA-RMM model with recent models. The results demonstrated that the MFPA-RMM model has accomplished enhanced results with higher values of NODT. In addition, it is noticed that the MFPA-RMM model has provided an increased NODT of 16854 whereas the EECBRM, LEACH, TEEN, DEEC, EAUCF, and FUCHAR models have attained reduced NODT of 16302, 15259, 7383, 12402, 10489, and 9246 respectively.

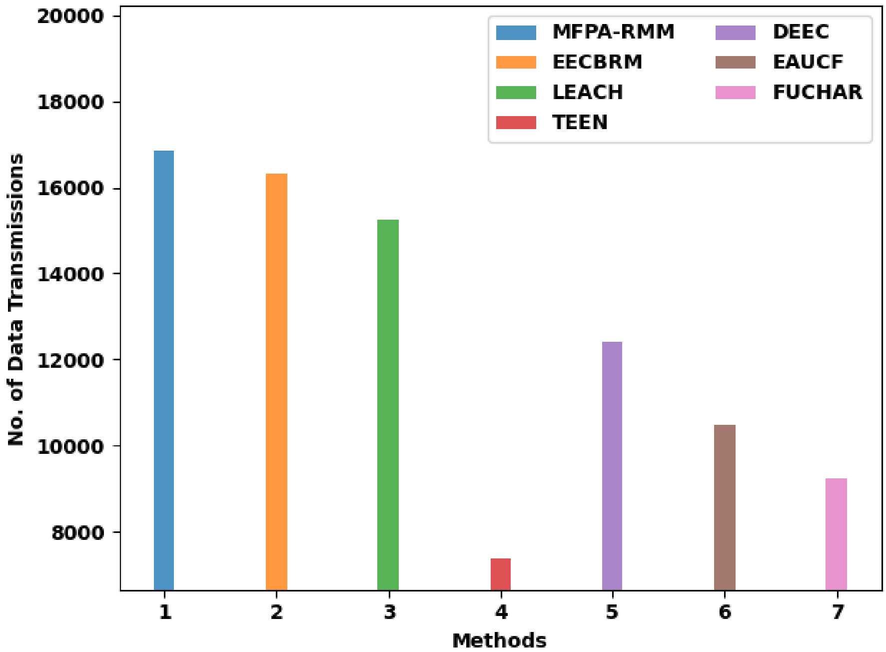

Figure4: Comparative NODT Inspection of MFPA-RMM Model

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Table 3: NODT Inspection of MFPA-RMM Model

Methods	No. of Data Transmissions
MFPA-RMM	16854
EECBRM	16302
LEACH	15259
TEEN	7383
DEEC	12402
EAUCF	10489
FUCHAR	9246

Table 4 and Fig. 5 provide the lifetime analysis of the MFPA-RMM model with recent models. Based on FND, the MFPA-RMM model has offered higher FND of 1791 whereas the LEACH, TEEN, DEEC, EAUCF, FUCHAR, and EECBRM models have obtained lower FND of 807, 1034, 1015, 1347, 1641, and 1727 respectively. Next, with respect to HND, the MFPA-RMM model has provided increased HND of 2031 whereas the LEACH, TEEN, DEEC, EAUCF, FUCHAR, and EECBRM models have resulted to reduced HND of 1139, 1096, 1063, 1518, 1812, and 1940 respectively. Finally, with respect to LND, the MFPA-RMM model has offered higher LND of 2284 whereas the LEACH, TEEN, DEEC, EAUCF, FUCHAR, and EECBRM models have obtained lower FND of 1295, 1352, 1390, 1532, 2092, and 2177 respectively.

Table 4: Lifetime Inspection of MFPA-RMM Model

No. of Rounds			
Methods	**FND**	**HND**	**LND**
LEACH	807	1139	1295
TEEN	1034	1096	1352
DEEC	1015	1063	1390
EAUCF	1347	1518	1532
FUCHAR	1641	1812	2092
EECBRM	1727	1940	2177
MFPA-RMM	1791	2031	2284

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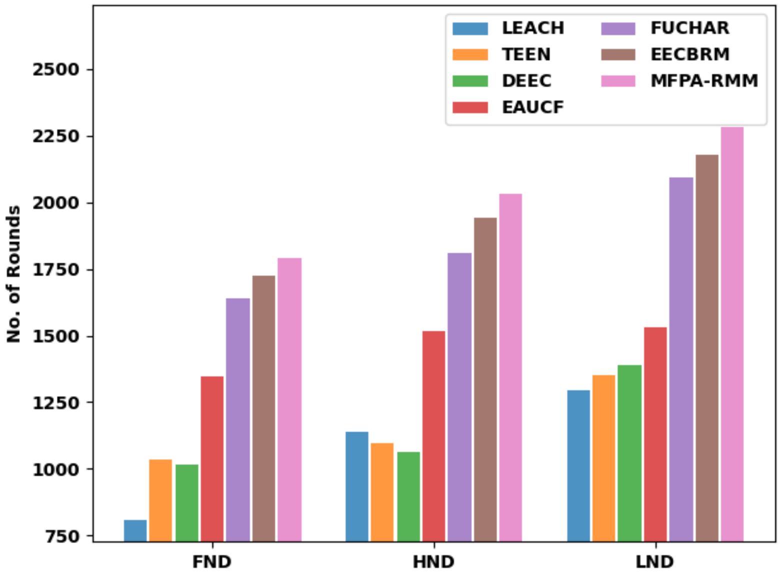

Figure 5: Comparative Lifetime Inspection of MFPA-RMM Model

5. Conclusion

This study has developed a novel MFPA-RMM model for Clustered IoT Environment. The presented MFPA-RMM model majorly focuses on the clustering the IoT devices in such a way that the resources are proficiently managed. The MFPA-RMM model is derived based on the FCM with FPA. The FPA approach is called as heuristic algorithm encompassed with the advantages of faster convergence and global optimization, therefore it is incorporated to FCM system for resolving the advantages and disadvantages of FCM method as termed as FCM-FPA mechanism. The result analysis of the MFPA-RMM model reported the enhanced performance of the MFPA-RMM model over other techniques. Therefore, the MFPA-RMM model can be exploited as an effectual tool for clustering the devices in the IoT environment. In future, data aggregation and compression schemes can be included to improve the efficiency of the presented network. In addition, security and privacy issues can be resolved in the future work.

References

[1] Abbas, F., Liu, G., Fan, P. and Khan, Z., 2020. An efficient cluster based resource management scheme and its performance analysis for V2X networks. IEEE Access, 8, pp.87071-87082.

[2] Munaye, Y.Y., Juang, R.T., Lin, H.P., Tarekegn, G.B. and Lin, D.B., 2021. Deep Reinforcement Learning Based Resource Management in UAV-Assisted IoT Networks. Applied Sciences, 11(5), p.2163.

[3] Sharma, M., Singla, M.K., Nijhawan, P. and Dhingra, A., 2021. Sensor-based optimization of energy efficiency in Internet of Things: A review. Sustainable Development Through Engineering Innovations, pp.153-161.

[4] Koo, S. and Lim, Y., 2021. A Cluster-Based Optimal Computation Offloading Decision Mechanism Using RL in the IIoT Field. Applied Sciences, 12(1), p.384.

[5] Geng, B., Li, Q. and Varshney, P.K., 2021. Utility-Theory-Based Optimal Resource Consumption for Inference in IoT Systems. IEEE Internet of Things Journal, 8(15), pp.12279-12288.

[6] Sharma, S. and Saini, H., 2020. Fog assisted task allocation and secure deduplication using 2FBO2 and MoWo in cluster-based industrial IoT (IIoT). Computer Communications, 152, pp.187-199.

[7] Salam, A., Javaid, Q. and Ahmad, M., 2021. Bio-inspired cluster–based optimal target identification using multiple unmanned aerial vehicles in smart precision agriculture. International Journal of Distributed Sensor Networks, 17(7), p.15501477211034071.

[8] Celik, E. and Dal, D., 2021. A novel simulated annealing-based optimization approach for cluster-based task scheduling. Cluster Computing, 24(4), pp.2927-2956.

[9] Apat, H.K., Bhaisare, K., Sahoo, B. and Maiti, P., 2020, March. Energy efficient resource management in fog computing supported medical cyber-physical system. In 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 1-6). IEEE.

DOI: https://doi.org/10.54216/IJWAC.040205
Received: March 27, 2022 Accepted: August 28, 2022

[10] Zahoor, S. and Mir, R.N., 2021. Resource management in pervasive Internet of Things: A survey. Journal of King Saud University-Computer and Information Sciences, 33(8), pp.921-935.
[11] Desai, P.R., Mini, S. and Tosh, D.K., 2022. Edge-based Optimal Routing in SDN-enabled Industrial Internet of Things. IEEE Internet of Things Journal.
[12] Jaiswal, K. and Anand, V., 2021. A Grey-Wolf based Optimized Clustering approach to improve QoS in wireless sensor networks for IoT applications. Peer-to-Peer Networking and Applications, 14(4), pp.1943-1962
[13] Dogra, R., Rani, S., Verma, S., Garg, S. and Hassan, M.M., 2021. TORM: Tunicate Swarm Algorithm-based Optimized Routing Mechanism in IoT-based Framework. Mobile Networks and Applications, pp.1-9
[14] Khalid, A., ul Ain, Q., Qasim, A. and Aziz, Z., 2021. QoS based optimal resource allocation and workload balancing for fog enabled IoT. Open Computer Science, 11(1), pp.262-274
[15] Jumnal, A. and SM, D.K., 2020, January. Energy aware cluster based optimal virtual machine placement in cloud environment. In 2020 Fourth International Conference on Inventive Systems and Control (ICISC) (pp. 266-271). IEEE
[16] Liu, X., Jia, M. and Na, Z., 2019, January. Optimal Resource Optimization for Cluster-Based Energy-Efficient Cognitive IoT. In International Conference on Wireless and Satellite Systems (pp. 532-540). Springer, Cham
[17] Yang, X.S., 2012, September. Flower pollination algorithm for global optimization. In International conference on unconventional computing and natural computation (pp. 240-249). Springer, Berlin, Heidelberg.

DOI: https://doi.org/10.54216/IJWAC.040205
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