Journal of Critical Reviews

ISSN- 2394-5125 Vol 7, Issue 14, 2020

A HEURISTIC DATA AGGREGATION IN HETEROGENEOUS LOW POWER DEVICES FOR INTERNET OF THINGS

[1]Dr.Y.Chitti Babu , [2]Dr.SUGANTHI SU , [3]Dr.R.KALPANA, [4]Dr.M.Nithya

[1]Associate Professor ,St.Ann's College Of Engineering &Technology ,AndhraPradesh
Email:chitti510@gmail.com

[2]Associate Professor, Dept. of ECE ,Sri Sai Ram Institute of Technology ,Chennai - 600044,India
[3]Professor/CSE ,Madanapalle Institute of Technology & Science,Madanapalle- Andhra Pradesh
[4]Professor & Head ,Department of Computer Science and Engineering,V.M.K.V Engineering College, Salem

Received: 06.04.2020 *Revised: 08.05.2020* *Accepted: 04.06.2020*

Abstract

Internet of Things (IoT) has been envisioned as smart objects' (things) communication and integration. The key challenge with regards to IoT is privacy. Within the IoT context, vertically-partitioned data learning is quite an applicable and well-known strategy. The issue happens whenever an event or state has to be predicted or identified, depending on the values assessed features at diverse nodes. An identity may be uncovered due to Quasi-Identifiers (QI), which are an attribute set of the information of a user. Wireless Sensor Network (WSN) is largely used as data collection for IoTs. Energy utilization can be decreased with data aggregation in WSN. In WSNs, an Energy-Efficient Hierarchical Clustering Algorithm (EEHCA) can attain good performance with regards to network lifespan through adjusting the nodal energy load and reducing the usage of energy for communication. Energy usage, load balance, and so on are sensor network performance factors which can be greatly boosted with the Particle Swarm Optimization (PSO) algorithm. In comparison to other mathematical and heuristic methods, this algorithm has better throughput and more efficient. Vertically-partitioned data aggregation that makes use of Quasi-Identifiers (QI) in the Internet of Things (IoT) has been proposed in this work and optimize the WSN using PSO to improve the performance of the entire system.

Keywords: Internet of Things (IoT), Privacy, Wireless Sensor network (WSNs), vertically partitioned data, Quasi-Identifiers (QI), Energy-Efficient Hierarchical Clustering Algorithm (EEHCA) and Particle Swarm Optimization (PSO).

DOI: http://dx.doi.org/10.31838/jcr.07.14.07

INTRODUCTION

For the wireless communication of tomorrow, an increasingly developing field is the Internet of Things (IoT). IoT's fundamental style is the ubiquitous presence of numerous surrounding objects or things like mobile phones, actuators, sensors, radio-frequency identification (RFID) tags, etc. With unique addressing schemes, shared objectives are accomplished by these objects or things through their interaction and cooperation with their neighbours. Despite that, the swift development of mobile internet services and wireless communications has made the performance improvement of existing IoT technology essential for accomplishing network coverage enhancement, low complexity, minimal cost, and other such requisites [1]. One key issue is preserving the privacy of the data stored in the IoT. Some of the techniques used for privacy preservation are encryption mechanisms, cryptographic algorithms, and the way data is stored. In vertically partitioned datasets, the features of data are stored in different sites; thus, combining the local datasets gives the global dataset.

Within the vertically-partitioned data scenario [4], there is a distribution of the observations' feature values, that is, the data table's columns across the nodes j = 1,...,m. The index column is just shared in a way that it is established which features correspond to which observation. This needs continuous object tracking for the actualization in the IoT through globally unique identifiers for every entity. The distributed columns across nodes comprise of the whole instance space's subspaces. These subspaces and their individual components (for example, features), in supervised learning inclusive of the target label, have a structure of dependency, which is often not known prior to learning. This scenario's learning hence may be viewed as an exponentially sized combinatorial problem, that is, which features subset offers most information regarding the target concept.

The definition of the Quasi-Identifier (QI) is the identifiable information of an individual that is merged with other information categories despite them not being a Direct Identifier (DID). QI is also significant personal information which needs a similar processing level as a DID. If there is QI de-identification of categorized information, there may be an occurrence of a huge amount of data loss, and there may be a large decrease of the data utilized for the actual analysis. Thus, critical challenges of de-identification [5] require appropriate selection of QIs and provision of the actual data essential for data analysis. As there is no definition of exact criteria for de-identification till data, the selection of the QIs occurs due to subjective judgments based on the person-in-charge's experience. Moreover, as the de-identification depends on diverse criteria, there is inconsistency in the QI election.

The clustering algorithm has been verified as an efficient technique in WSN for network lifespan prolongation, nodal energy usage balance, and minimization of nodal energy dissipation when compared with flat routing algorithms. The organization of all the sensor nodes into groups known as clusters and the operation time duration is partitioned into certain rounds [2] in the clustered-in networks. Cluster formation and cluster operation are the two stages which constitute each round. Through competition, there is a selection of certain cluster-heads during the cluster formation stage. During the cluster operation stage, the cluster-heads are forwarded to the member nodes' monitoring data, and later, the aggregated results are sent in a single hop or multi-hop manner towards the sink node. To accomplish the overall network's load balance effect, at the end of every round, competition has to be carried out by all the nodes need for the new cluster-head selection.

Cluster-based technique [3] is treated as a hierarchical method where the entire network is partitioned into numerous clusters.

However, the network will bottleneck due to clustering, which in turn leads to additional delays during the data aggregation process. Clustering is a significant method for energy efficacy enhancement and data redundancy removal. This technique also aids in prolongation of the WSN lifetime. Moreover, network traffic can be minimized with effective data aggregation protocol. More than one sensor may be able to detect a specific objective that occurs in a specific area.

Issues related to 'spam' and energy utilization may be caused by the huge number of devices in the IoT. As the IoT system is dynamic and complex, various SI algorithms have been devised for using simple individuals for the computation of these complex activities. Global optimization can be accomplished by adopting the SI-based algorithm as a group of simple devices through IoT system [7] modelling. Cloud computing also has a significant role in data analysis, depending on the immense data amount gained from IoT systems. By applying SI to cloud computing applications, there is facilitation of the resolution of problems which involve multi-objective optimization.

A swarm intelligence-inspired optimization approach which constitutes an artificial intelligence category is the Particle Swarm Optimization (PSO) algorithm which has been devised from studying the predatory birds' behaviour. The PSO algorithm's fundamental principle is that every bird is treated as a particle, and the outcome which is optimized will correspond to the particle's position in the search space [8]. There is an update of the particle at every iteration stage through tracking two extremes, which are, the local solution's best position and the global optimal solution's best position. The subsequent step of the direction and flight speed is determined by the learning experience of the particles and the information exchange of every particles. Eventually, there will be a motion towards the global optimal solution. As a result, the performance of WSNs with regards to metrics such as energy utilization, lad balance, and so on, can be greatly enhanced greatly with the establishment of the PSO algorithm.

A hybrid Energy Efficient Hierarchical Clustering Algorithm (EEHCA) and PSO approach is proposed in this work. The rest of this investigation has been organized in the following manner. All related literary works have been duly discussed in Section 2. The employed methods have been explained in Section 3. The experimental results have been discussed in detail in Section 4.

LITERATURE SURVEY

Jeong et al. [9] recommended a strategy which denotes when to transmit the data determined by prediction of a node's residual energy, and aggregates sensed data for maximizing the data amount that reaches the sink node. In this strategy, if the estimated nodal residual energy is expected to exceed the capacity, either the aggregated data will get transferred or the radio gets switched off and just the sensed data is stored for reducing the nodes' blackout time. Simulation outcomes demonstrate that the proposed strategy minimizes the nodes' blackout time and effectively maximizes the rate of data aggregation in comparison with both the specific amount of aggregated data sending and the normal data sending cases.

There is random exchange of the between diverse devices in the communication approach. During information exchange, at every node level, there is dissipation of energy. While the traditional models of the clustering approach were recommended for attaining optimal resource utilization, the network's dynamic node behaviour provides a synchronized behaviour in the network which leads to larger dissipation of energy. Mohan & Bhaskara [10] devised a novel energy conservation model for a network which has random distribution in order to overcome this problem. A novel scheduling methodology was developed for minimum dissipation of energy in the communication approach for IoT applications.

Issues related to energy efficiency were discussed by Rani et al. [11] through proposal for a novel deployment scheme which introduced the following: (1) a network design that was hierarchical in nature, (2) an IoT model that was efficient in energy, (3) and a transmission algorithm that had minimum energy utilization for the optimal model's implementation. Compared to the conventional WSN schemes, the experimental outcomes demonstrated that the new scheme was flexible and had more energy efficiency, and subsequently could be deployed for efficient IoT communication.

Distributed sensor data's privacy-boosting aggregation like traffic information or residential energy utilization is the focus of the research and challenge handled by Bennati & Pournaras [12]. Citizens can select the level of privacy by decreasing the shared data's quality at a cost of a lesser accuracy in services related to data analytics. A baseline scenario is taken in account where the data of the IoT sensor will be directly shared with a central aggregator who is not trustworthy. There is introduction of a grouping mechanism which enhances the privacy through initially sharing the aggregated at a group level in contrast to a baseline scenario where there is direct data sharing of each individual shares with a central aggregator. The sensor data of individuals get obscured by group-level aggregation akin to homomorphic encryption and differential privacyschemes. As a result, privacy-sensitive information inference from single sensors becomes more difficult computationally in comparison to the baseline scenario. The assessment of the proposed system and its typical applicability is done by utilizing real-world data from two smart city pilot projects. There is increase of the privacy with grouping, whilst retaining the baseline scenario's accuracy. Intra-group influences of privacy of one member of the group on the other members are evaluated and privacy fairness has been observed to be increased between members of the group who have the same choices of privacy. There is comparison of numerous strategies of grouping. The largest gains of privacy have been offered through grouping by proximity of privacy choices. There is also discussions on the impacts of the the incentive mechanism's design.

For sensor networks with long lifespans, Xin et al. [13] proposed a hierarchical clustering algorithm. An Energy-Efficient Hierarchical Clustering Algorithm (EEHCA) for WSNs accomplishes good performance with regards to network longevity through decrease of the communication energy usage and nodal load balancing. Frequent cluster-head election can be prevented using the EEHCA's novel method for election of cluster-head. There is presentation of the backup cluster concept so as to boost the fault-tolerance performance. Moreover, when nodes have completed communicating within their own clusters and the data aggregation has been completed by the cluster-heads, aggregated data is transferred by the head clusters to the sink node using a special multi-hop mode. In comparison to the Low Energy Adaptive Clustering Hierarchy (LEACH), and the Hybrid Energy-Efficient Distributed clustering (HEED), experimental outcomes demonstrate that, with regards to network lifespan, the EEHCA's performance is better.

An efficient Quasi-identifier index-based approach was developed by Zhang et al. [14] to accomplish high data utility over distributed and incremental data sets and to guarantee preservation of privacy. For the purpose of efficiency, there is indexing of the Quasi-identifiers, that denote anonymized data groups. Thus, an algorithm has been developed to satisfy the approach accordingly. In comparison to existing approaches, the experimental outcomes have demonstrated that the proposed approach has better improvements in the efficacy of privacy preservation on large-volume incremental data sets.

An Enhanced PSO-Based Clustering Energy Optimization (EPSO-CEO) algorithm for the WSN has been proposed by Vimalarani et al. [15] . The proposed technique employs the PSO algorithm to

carry out the clustering and election of the cluster-head for reducing the WSN's utilization of power. For validation of the energy utilization decrease, the performance factors are assessed and outcomes are compared against the competitive clustering algorithm.

The Hierarchical Data Aggregation with Particle Swarm Optimization (HDA-PSO) for WSNs was proposed in Yin et al. [16] to circumvent the issue of energy hole and also to prolong the network lifespan. Initially, design of the fitness function is done based on multiple relational matrices such as the coverage area's centroid degree, the average distance amongst adjacent nodes, and the residual energy. Next, for efficiently encircling the optimal solution with an initial position of particles, a population initialization approach is proposed that depends on beta distribution as per the sensor network's distribution characteristics of nodes. Then, there is introduction of a novel operator which relies on differential evolution for updating the velocity in order to efficiently adjust the particle swarm optimization's exploration and evolution. Experimental outcomes demonstrate that the proposed algorithm is able to efficiently balance the nodes' energy usage under diverse densities of nodes, boost the efficiency of energy , and also significantly extend the network longevity.

METHODOLOGY

Clustering's key objective is the minimization of the whole power of transmission across a specific path's nodes, and the maintenance of load balance amongst the nodes in order to prolong the lifespan of the network.

Vertical Partitioning and Encryption for Privacy-Preserving

The dataset is randomly split vertically into three datasets linked by unique entity id. The data is generalized in each dataset using the QI. During the collation of the data, there may be probability of revelation of the information subject's identity by attacks on privacy attacks like linkage attacks. Standard QIs include age, zipcode, area, profession, and so on. The election of the QIs relies on the guidelines for de-identification of individual information to abide by the criteria for avoiding re-identification of the information. Hence, there has to be establishment of a QI election technique taking into account the QI characteristics, distribution range, and medical data, provided that there will be decreased data usage as a result of majority of the data being suppressed when there are QI election and de-identification [6] of all defined example items. Most of the existing QI-related research constitutes the target data's comparison and analysis, and there is recommendation of data on new de-identification targets depending on the outcomes. The vertically split with the highest number of QI is taken into consideration, and the QI is encrypted with the Data Encryption Standard (DES) algorithm. The DES uses a key to encrypt and decrypt the data. A 64-bit key is used in DES.

Energy Efficient Hierarchical Clustering (EEHCA) Routing

Hierarchical Routing Protocols are communication protocols which are energy efficient. Sensor nodes utilize these protocols for transmission of data to the Base Station (that is, the sink). These protocols' primary objective is the productive utilization of the sensor node's energy usage when connecting them in multi-hop communication within a specific cluster. The number of message transmissions to the sink can be decreased through execution of data aggregation and data fusion. As a result, the energy utilization can be minimized.

In the EEHCA protocol [17], every sensor node in a network will transform into a cluster-head by probability p. Also, data is sent to other nodes such that this node is a cluster-head within the radio's range. These CH-cluster heads are termed as volunteer cluster heads (CH). There is election of a cluster of a closest cluster-head by any sensor node that obtains these data and which is also not a CH-cluster-head within a provided range. Some of the sensor nodes that are neither CH-cluster heads nor have been chosen by any cluster would transform into a CH-cluster head. These cluster types are known as forced cluster heads. Because of comprising of delimited information that transmits to k hops, and if the sensor node is incapable of detecting the CH which transfers the data within a period of time t, it can wrap up that it was not within a range of the k hops of further volunteer cluster head also will seem to be the forced cluster head. A cluster-head can supervise its communication by restriction of its number of hops.

Proposed Particle Swarm Optimization (PSO) Routing

In 1995 [18], American psychologist Kennedy and electrical engineer Eberhart initially proposed the Particle Swarm Optimization (PSO). This algorithm is a biomimetic intelligent technique that replicates the foraging behaviour of bird colonies. Essentially, this is a group intelligence-based random optimization algorithm that utilizes the bird group's individual sharing mechanism and compels the whole group to evolve from an disorganized mode to an more orderly mode [16]. Eventually, there are several iteration of the algorithm in order to identify the problem solving space's global optimal solution. Initially, a bird group's each individual is treated as particles in a D dimension space irrespective of weight and volume. There is random initialization of the particles in the search space. These particles pursue the best position. The speed of motion determines the motion's distance and direction. During the iterative phases, there is constant update of the particles' global extremes and individual fitness values in order to use the iterative cycle to gain the optimal solution.

There is initialization of a system's random solutions with a population and search optimal solutions in every generation. Particles are referred to every generation's probable solutions. The PSO's each particle retains a stored record of all its coordinates that are associated with getting the better solution through pursuing the existing best particles. Each particle's fitness function is carried out and there is evaluation and storage of the value of fitness (best solution). pbest is the term used to refer to the existing optimum particle's value of fitness. The PSO's optimization of the best population value which is gained till date by any particle in the neighbourhood and its locality is referred to as the lbest. A certain particle treats every generated population as its topological neighbours. From the generated population, there is selection of the best value. The best solution will be this particular best value. gbest is the term used to refer to this best solution.

PSO [15] constantly attempts to alter each particle's velocity in the direction of its lbest and pbest. Random technologies determine the velocity through generation of random numbers that move in the direction of the localities of lbest and pbest. For problem solving, the best solution is chosen from the huge generated solutions' collection. The storage and maintenance of a record of outcomes for the PSO algorithm's three global variables like stopping value, gbest, and target value or condition is always done.

To optimize the cluster head selection in the EEHC, the PSO is applied. The PSO particles are encoded with the position of nodes and velocity. The fitness of each particle is computed based on the distance from cluster heads and energy of the nodes. The new position and velocity is updated in each iteration forming new particles/solutions. Fitness is updated and the algorithm iterates till termination criteria is met. The output gives the optimal set of cluster heads.

RESULTS AND DISCUSSION

Table 1 shows the simulation parameters. Table 1 shows the results for dead nodes. Table 3 to 5 and figure 1 to 3 shows the Residual energy (joule) - Normal Nodes, Residual energy (joule) -

Super Nodes and Residual energy (joule) - Advanced Nodes respectively.

Table 1 Simulation Parameters

Parameters	Values
Area	1500 x 1500 m^2
BS location	Center
Nodes (n)	3000

Table 2 Results for Dead Nodes

Round	First dead node	90% dead node
EEHCA	1023	1230
PSO	1213	1736

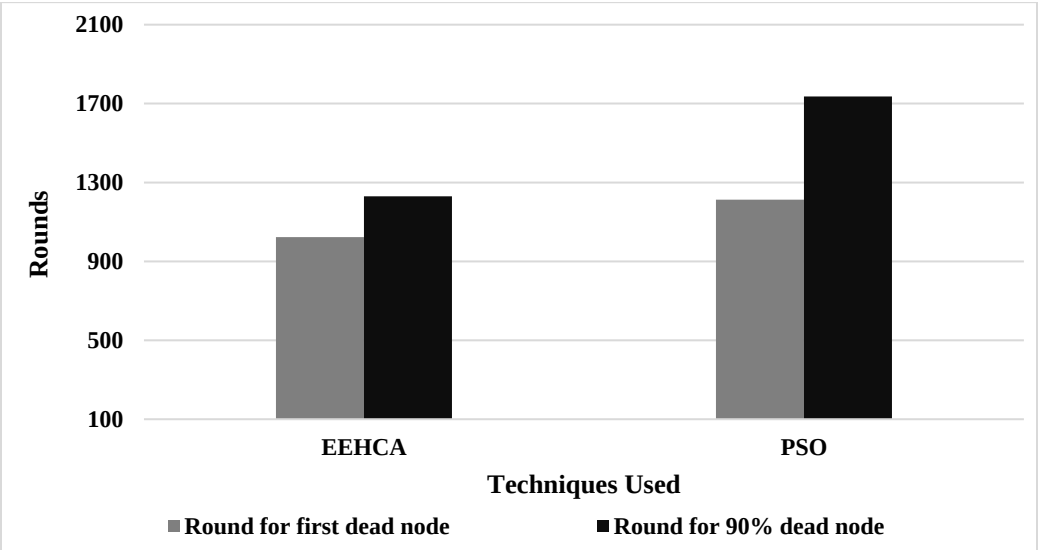

Figure 1 Results for Dead Nodes

Table 2 and figure 1 shows that the proposed PSO performs better because the nodes are dead only after 1213 and 1736 number of rounds than EEHCA for 90% dead nodes. It is seen that the nodes are dying much later in proposed PSO than EEHCA for first dead nodes.

Table 3 Residual energy (joule) - Normal Nodes for PSO

Residual energy (joule)- Normal Nodes	EEHCA	PSO
0	0.6	0.6
300	0.46	0.49
600	0.41	0.46
900	0.27	0.38
1200	0.13	0.32
1500	0.06	0.15
1800	0	0.02
2100	0	0
2400	0	0
2700	0	0
3000	0	0

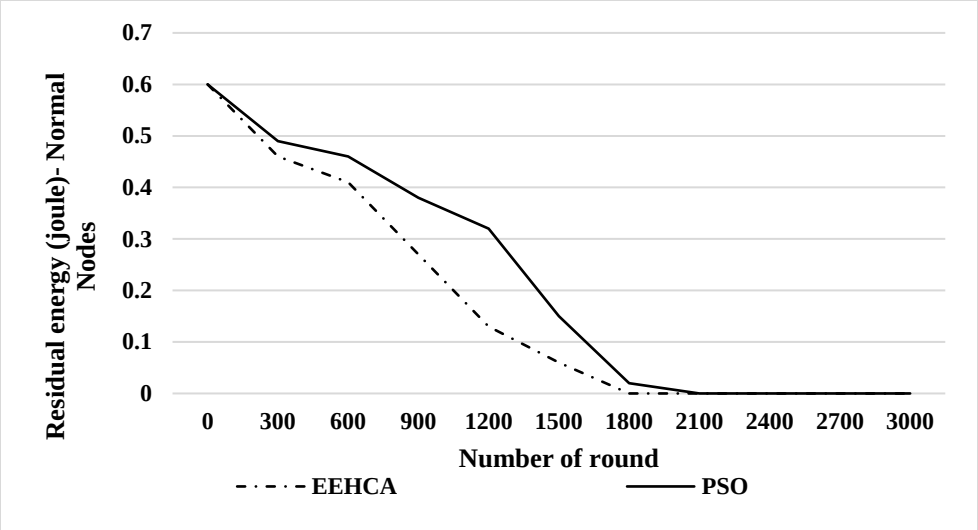

Figure 2 Residual energy (joule) - Normal Nodes for PSO

Table 3 and figure 2 shows that the Residual energy (joule) - Normal Nodes of Greedy EEHCA performs better by 6.32% than EEHCA at number of rounds 300. The Residual energy (joule) - Normal Nodes of Greedy EEHCA performs better by 33.85% than EEHCA at number of rounds 900. The Residual energy (joule) - Normal Nodes of Greedy EEHCA performs better by 85.7% than EEHCA at number of rounds 1500.

Table 4 Residual energy (joule) - Super Nodes for PSO

Residual energy (joule)- Super Nodes	EEHCA	PSO
0	0.8	0.8
300	0.78	0.79
600	0.61	0.72
900	0.44	0.68
1200	0.31	0.47
1500	0.3	0.33
1800	0.16	0.31
2100	0.1	0.3
2400	0	0.1
2700	0	0
3000	0	0

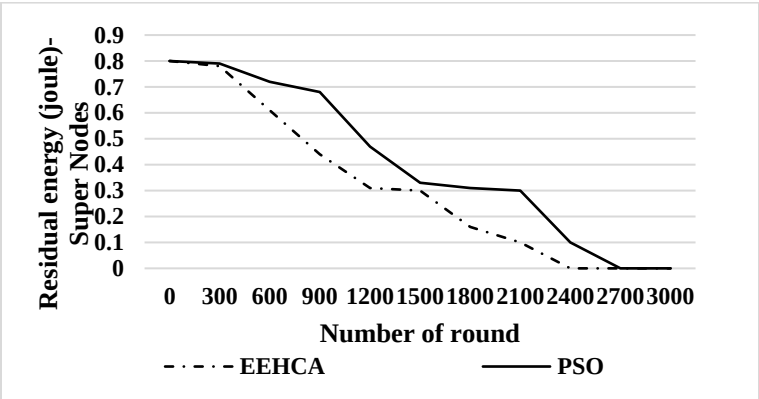

Figure 3 Residual energy (joule) - Super Nodes for PSO

Table 4 and figure 3 shows that the Residual energy (joule) - Super Nodes of Greedy EEHCA performs better by 1.3% than EEHCA at number of rounds 300. The Residual energy (joule) – Super Nodes of Greedy EEHCA performs better by 42.9% than EEHCA at number of rounds 900. The Residual energy (joule) - Super Nodes of Greedy EEHCA performs better by 9.5% than EEHCA at number of rounds 1500.

Table 5 Residual energy (joule) - Advanced Nodes PSO

Residual energy (joule)- Advanced Nodes	EEHCA	PSO
0	1.2	1.2
250	1.07	1.12
500	0.9	1.03
750	0.75	0.99
1000	0.62	0.77
1250	0.62	0.64
1500	0.33	0.61
1750	0.23	0.6
2000	0.13	0.29
2250	0	0.2
2500	0	0.1

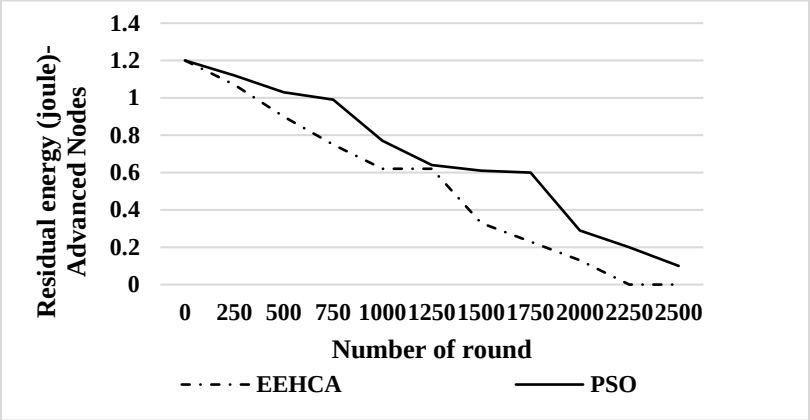

Figure 4 Residual energy (joule) - Advanced Nodes for PSO

Table 5 and figure 4 shows that Residual energy (joule) - Advanced Nodes of Greedy EEHCA performs better by 4.57% than EEHCA at number of rounds 250. The Residual energy (joule) - Advanced Nodes of Greedy EEHCA performs better by 27.6% than EEHCA at number of rounds 750. The Residual energy (joule) - Advanced Nodes of Greedy EEHCA performs better by 59.6% than EEHCA at number of rounds 1500. The Residual energy (joule) - Advanced Nodes of Greedy EEHCA performs better by 76.2% than EEHCA at number of rounds 2000.

CONCLUSION

Communication load reduction and data redundancy elimination can be accomplished with data aggregation. There has been comprehensive exploitation of the hierarchical clustering mechanisms due to their effectiveness in data latency reduction and network scalability maximization. Through balancing of the nodal energy load and reducing of the communicational energy usage, good performance with regards to network lifetime can be attained by the EEHCA. An optimization method that takes into account the social behaviour of natural species for computational purposes is the Particle Swarm Optimization. Experimental results demonstrate that, at number of rounds 300, the Residual Energy (Joule)-Normal Nodes of Greedy EEHCA functions better by 6.32% compared to the EEHCA. At number of rounds 900, the Residual Energy (Joule)-Normal Nodes of Greedy EEHCA functions better by 33.85% compared to the EEHCA. Moreover, at number of rounds 1500, the Residual Energy (Joule)-Normal Nodes of Greedy EEHCA functions better by 85.7% compared to the EEHCA.

REFERENCES:

1. Sathish Kumar, Mukesh A Zaveri, "Hierarchical Clustering for Dynamic and Heterogeneous Internet of Things", Procedia Computer Science 93 (2016) 276 – 282.
2. Thilagavathi S, Gnanasambandan Geetha B (2015) Energy aware swarm optimization with inter-cluster search for wireless sensor network. Sci World J 25:1–8.
3. Hariharan, R., Mahesh, C., Prasenna, P., & Kumar, R. V. (2016). Enhancing privacy preservation in data mining using cluster based greedy method in hierarchical approach. Indian Journal of Science and Technology, 9(3), 1-8.
4. M. Stolpe, K. Bhaduri, K. Das, and K. Morik. Anomaly Detection in Vertically Partitioned Data by Distributed Core Vector Machines. In H. Blockeel, K.Kersting, S.Njissen, andF.Železný, editors, Proc. of the European Conf. on Machine Learning and Knowledge Discovery in Databases (ECML/PKDD), pages 321–336, Berlin, Heidelberg, 2013. Springer.
5. Y.J. Lee, K.H. Lee, Re-identification of medical records by optimum quasi-identifiers, Advanced Communication Technology (ICACT), 2017 19th International Conference on, IEEE, 2017, pp. 428- 435.
6. A.M. Omer, M.M.B. Mohamad, Simple And Effective Method For Selecting Quasi identifier, Journal of Theoretical and Applied Information Technology, 89 (2016) 512.
7. Sun, W., Tang, M., Zhang, L., Huo, Z., & Shu, L. (2020). A survey of using swarm intelligence algorithms in IoT. Sensors, 20(5), 1420.
8. Wang, J., Cao, Y., Li, B., Kim, H. J., & Lee, S. (2017). Particle swarm optimization based clustering algorithm with mobile sink for WSNs. Future Generation Computer Systems, 76, 452-457.

9. Jeong, S., Kim, H., Noh, D. K., & Yoon, I. (2016, October). Energy-aware data aggregation scheme for energy-harvesting wireless sensor networks. In 2016 First IEEE International Conference on Computer Communication and the Internet (ICCCI) (pp. 140-143). IEEE.
10. Mohan, A., & Bhaskara, B. Energy Efficient Hierarchical Clustering for Dynamic and Heterogeneous Internet of things.
11. Rani, S., Talwar, R., Malhotra, J., Ahmed, S. H., Sarkar, M., & Song, H. (2015). A novel scheme for an energy efficient Internet of Things based on wireless sensor networks. Sensors, 15(11), 28603-28626.
12. Bennati, S., & Pournaras, E. (2018). Privacy-enhancing aggregation of Internet of Things data via sensors grouping. Sustainable cities and society, 39, 387-400.
13. Xin, G., HuaYang, W., & DeGang, B. (2008). EEHCA: An Energy—Efficient Hierarchical Clustering Algorithm for Wireless Sensor Networks. Information Technology Journal, 7(2), 245-252.
14. Tekuri, S.K., Pasupuleti, S.K., Konidala, K.K., Pabbaraju, N.Pharmacological Effects of Polyalthia cerasoides (Roxb.) Bedd.: A brief Review(2019) Journal of Complementary Medicine Research, 10 (1), pp. 38-49.
15. Vimalarani, C., Subramanian, R., & Sivanandam, S. N. (2016). An enhanced PSO-based clustering energy optimization algorithm for wireless sensor network. The Scientific World Journal, 2016.
16. Yin, X., Li, S., & Lin, Y. (2019). A Novel Hierarchical Data Aggregation with Particle Swarm Optimization for Internet of Things. Mobile Networks and Applications, 24(6), 1994-2001.
17. Bandyopadhyay, S., & Coyle, E. J. (2003, March). An energy efficient hierarchical clustering algorithm for wireless sensor networks. In IEEE INFOCOM 2003. Twenty-second Annual Joint Conference of the IEEE Computer and Communications Societies (IEEE Cat. No. 03CH37428) (Vol. 3, pp. 1713-1723). IEEE.
18. Kennedy J, Eberhart R. (1995) Particle swarm optimization, In: Proceedings of IEEE International Conference on Neural Networks, 1942–1948.