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An Energy Efficient e-Healthcare Framework Supported by Novel EO-μGA (Extremal Optimization Tuned Micro-Genetic Algorithm)

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Abstract
The edge/fog computing has the potential to gear up the healthcare industry by providing better and faster health services to the patients. In healthcare systems where every second is crucial, the edge computing can be helpful to reduce the time between data capture and analytics in a powerful manner. In edge computing, the network edge devices are configured in such a manner that they can handle critical analysis and make necessary decisions instead of sending the captured health data directly to the cloud. However, lifetime of the edge network is a critical factor and thus an energy efficient network architecture has to be designed to achieve the above mentioned goal. In this regard, this research presents a new extremal optimization tuned micro genetic algorithm (EO-μGA) based clustering technique for the sake of efficient routing and prolonging network lifetime by saving the battery power of network edge devices. Moreover, a novel fitness function with a set of relevant criteria of edge devices such as energy factor, average intra-cluster distance, average distance to cluster leader over data analytics center, average sleeping time, and computational load has been considered for the selection of the cluster leader which will be responsible for managing intra-cluster and inter-cluster data communication. The simulation results show that the proposed EO-μGA based clustering model offers a higher network lifetime and a least amount of transmission energy consumption per node as compared to various state of the art optimization algorithms.

Keywords E-healthcare · Extremal optimization · Fog computing · Micro-genetic algorithm

1 Introduction

IoT has been chosen as the most attractive technology for healthcare sector to make it more attractive, effective and robust. It has been applied in numerous medical applications such as from remote health monitoring to chronic diseases, and elderly care etc. Moreover, it has the potential to provide treatment and medication at home through various medical devices, wearable sensors, diagnostic and imaging devices (Rahmani et al. 2018; Whitmore et al. 2015). Thus by incorporating IoT technology, the traditional healthcare is changing to be smarter every day and also expected to alleviate costs, increase the quality of life, and enrich the user's experience as well (Verma and Sood 2018). In an e-Healthcare system, IoT devices and sensors collect the data from various patients and surroundings about various parameters for analyzing the patient health condition and take necessary actions against it. Therefore, the continuous monitoring of patients through numerous sensors and devices is very much necessary. In this regard, a properly designed network is the most important factor for improving the lifetime of the IoT network. Thus, there is an utmost need for an efficient network architecture that can ensure a long lifetime of an e-Healthcare system. In this regard, the edge/fog computing has the potential to gear up the healthcare industry by providing better and faster health services to the patients (Rahmani et al. 2018; Majumdar et al. 2018). In healthcare systems where every second is crucial, the edge computing can be helpful to reduce the time between data capture and analytics in a powerful manner. In edge computing, the network edge devices are configured in such a manner that they can handle critical analysis and make necessary decisions instead of sending the captured health data directly to the cloud. However, lifetime of the edge network is a

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critical factor and thus a stable efficient network architecture has to be designed to achieve the above mentioned goal. So, clustering of edge devices into distinct clusters can be a proficient way of improving energy efficiency of the network, thereby providing health services for a long time (Majumdar et al. 2019). Cluster head based communication is a commonly followed method in wireless sensor network (WSN) for prolonging the network life time. This paper also addresses the clustering protocol like WSN but for the edge device network. In WSN the clustering is performed locally in the network where-as clustering in edge network can be considered as globally in the network. Furthermore, clustering in edge devices enables distributed edge analytics. It has an added advantage of having faster and real-time analysis of data in any large geographical region. This leads to a faster fault response time.

In this paper, a fog layer configured e-Healthcare architecture, consisting of a pool of Micro Data Centers (MDC) as edge devices has been proposed. These MDCs are entrusted with the responsibility of temporary and frequent processing of data and are deployed in various areas depending on the data collection needs. Every MDC is connected with some smart sensors or devices and are used to acquire health information of patients and transmit it to the cloud. As it is battery operated, there is a chance of network failure and hence may cause an extremely crucial health data loss. Taking into account the problems mentioned above, an energy efficient MDC network has been designed that can prolong the overall lifetime of the network and reduce the transmission time.

The key contributions of this paper has been given as follows:

a) A fog layer configured e-Healthcare model and strategy equipped with energy efficient edge devices has been designed.
b) A fast hybrid meta-heuristic algorithm named extremal optimization tuned micro genetic algorithm (EO-μGA) has also been proposed that partitions the network into distinct clusters of participating edge devices within the network in such a way that each cluster will have equally good fitness. The goodness of the employed strategy over other state of the art methods for prolonging the edge network lifetime has also been studied.
c) A novel fitness function associated with all the necessary criteria has been proposed for optimization of the edge network and selection of most promising edge devices in each cluster. This process determines the life of cluster as well as the whole MDC based healthcare network.

The rest of the paper is organized as follows: Section 2 addresses the background related to this research. Section 3 presents the related research works in the relevant field in detail. The proposed energy efficient clustering technique has been presented precisely in Section 4. Section 5 presents results and analysis part of this research. The paper has been concluded in Section 6.

2 Background

2.1 Micro Genetic Algorithm (μGA)

In case of binary coded Simple Genetic Algorithm (SGA), there may be a chance to obtain global optimal solution but at a slow convergence rate. Hence, in real-world problems where convergence speed is given priority, SGA cannot be useful. For example, in online optimization problems, the objective function may change faster than the SGA reaches to the optimal solution. In this regard, a faster GA is sincerely needed to support the online optimization. Micro Genetic Algorithm (μGA) is a kind of Genetic algorithm with a small population which was first introduced by Krishnakumar (Krishnakumar 1990). In μGA, the crossover operation takes place, but mutation operation is not required to be applied since enough diversity has already been maintained after convergence of μ population.

2.2 Extremal Optimization (EO)

The Extremal optimization is based on self-organized criticality concept in which successive replacement of the most undesirable variables in a suboptimal solution is done with newly generated random ones. EO is also inspired by the fact of physical instinct to optimize, which is generally followed by its ancestors, such as simulated annealing (SA) or genetic algorithms (GA) (Boettcher and Percus 2003).

2.3 Analytic Hierarchy Process (AHP)

AHP is a powerful and robust multi-criteria decision making (MCDM) technique that has been widely used in making and analyzing complex decisions in various applications. It is basically based on pair-wise comparisons in which problems are decomposed into a hierarchy of factors and criteria. It is also treated as an effective tool which helps in deriving weights for each evaluation criteria using matrix-oriented methods according to the decision maker's pairwise comparisons of the criteria. The higher the weight, the more important the corresponding criterion. The final task of alternative ranking involves relative weights aggregation of the decision elements that yields a final score for each option.

3 Related Research

This section is divided into two sub-sections which are the use of Internet of Things and Cloud/Fog computing in the healthcare domain, and different energy efficient techniques related to IoT. The first sub-section discusses the IoT and Cloud/Fog computing-based systems and frameworks in the healthcare domain. In the second, a survey of different energy efficient methodologies used for several IoT enabled systems has been illustrated.

3.1 IoT and Cloud-Based Healthcare

In 2018, Rahmani et al. (Rahmani et al. 2018) implemented a Smart e-Health Gateway architecture called UT-GATE based on the amalgamation of Fog computing with IoT. The system has the potential to offer several higher-level services such as local storage, embedded data mining, and real-time local data processing etc. Moreover, the authors have also demonstrated the fog-assisted system with a medical case study called Early Warning Scores (EWS) to monitor the patients with acute illness. In 2018, Majumdar et al. (Majumdar et al. 2018) designed an edge device configured e-Healthcare framework for remotely classifying the status of a highly epidemic disease named Kyasanur Forest Disease (KFD). They introduced the concept of smart edge devices configured with their proposed classification algorithm named extremal optimization tuned neural network (EO-NN). EO-NN achieved better performance in classification as compared to various state of the art classification techniques. In 2017, Hossain (Hossain 2017) proposed a scalable and efficient real-time patient monitoring system by using smartphones to acquire voice and electroencephalogram signals. Additionally, a cloud-supported appropriate indoor localization of the patients has also presented in this work by incorporating the concept of Gaussian mixture modeling. In 2017, Verma and Sood (Verma and Sood 2018) proposed an IoT equipped disease diagnosis framework wherein User Diagnosis Results (UDR) have computed on the server side. Additionally, authors have compared the performance of various classifiers on the dataset of numerous diseases collected from UCI database and also established an alert generation mechanism to handle the disease severity. In 2017, Chen et al. (Chen et al. 2017) proposed three novel algorithms for three different purposes to improvise the power management for IoT in E- Healthcare system. The power level decision (PLD) algorithm and a power level and packet size decision (PPD) algorithm have been used to minimize the energy consumption during data transmission and to decide the optimal packet size respectively. Moreover, a global link decision (GLD) scheme have also been proposed by the authors to improve factors such as network reliability, delay, and network lifetime. In 2017, Bhatia and Sood (Bhatia and Sood 2017) established an intelligent healthcare framework having the potential to analyze real-time health status and predict undesired health state vulnerability. For the implementation, authors have used various sensors to acquire the health data and also used Artificial Neural Network (ANN) model for the Prediction. In 2016, Hossain and Muhammad (Hossain and Muhammad 2016) described a cloud-assisted Healthcare monitoring system, named as Industrial IoT (HealthIIoT). This system offered real-time monitoring and analysis of patient's health-related data through mobile devices and sensors to avoid obnoxious circumstances. Moreover, to provide high-quality service and make the system secure, the healthcare data have been watermarked before being sent to the cloud. In 2015, Gelogo et al. (Gelogo et al. 2015) proposed an IoT based health monitoring application with the support of mobile gateway, named as u-healthcare. The authors have also presented an ideological framework of IoT that works for u-healthcare. In 2015, Santos et al. (Santos et al. 2015) introduced an IoT based healthcare system wherein Constrained Application Protocol (CoAP) and IEEE 11073 standards have been used for sharing of sensor data among different personal health devices and mobiles. In 2005, Barger and Brown et al. (Barger et al. 2005) developed a Smart-House system which was mainly concerned about proactive health monitoring of the elderly population by deploying remote monitoring technologies in their homes. The prototype was examined within a subject's home to detect behavioral patterns by using basic sensors and found satisfactory results. In 2015, Hussain et al. (Hussain et al. 2015) proposed a people-centric sensing framework for elderly and disabled people. Their methodology aims to provide a service-oriented emergency response in case of any abnormal condition of the patient. In 2015, Catarinucci et al. (Catarinucci et al. 2015) proposed an IoT enabled smart hospital system (SHS) by incorporating different technologies such as RFID, WSN, and smart mobile. For the data transmission at different scenarios authors have suggested to use different network infrastructures such as Constrained Application Protocol (CoAP), IPv6 over low-power wireless personal area network (6LoWPAN), and representational state transfer (REST).

3.2 Energy Efficient IoT Network

In 2014, a clear idea of IoT and its various possible applications was depicted by Gubbi et al. (Jin et al. 2014). The authors also highlighted the technological perspective of a need for energy management in IoT application areas. Moreover, they discussed several possible solutions of energy sources that can be followed in different applications. Since then, this topic has been taken as a research challenge by many researchers and lot of ideas related to this issue have been suggested till now. In 2016, Akgul et al. (Akgül and Canberk 2016) proposed a concept of smart and selfconfigured sensors which not only have the ability to optimize and heal itself but also capable of putting itself into sleep mode whenever necessary. In this way, it confirms a significant amount of energy saving. In 2014, a tree-based architecture named “energy-efficient index tree” was proposed to save the energy of a pool of geographically distributed sensors (Zhou et al. 2014). In this regard, the authors were concerned about the saving of sensors energy utilized for data acquisition, aggregation and query handling. In this approach, all the participating sensors were organized into a tree structure that manages the query transmission between sensors and the base station in an energy efficient manner. Similarly, in 2014, Tang et al. (Tang et al. 2014) presented another tree-based model in which the IoT region was partitioned into several grid cells that were organized hierarchically to form a tree. They had restricted the data transmission in such a way that sensors will only transmit data if any changes occur in the currently detected value as compared to the previously sent value. Researchers also tried to improve the battery energy efficiency by configuring the sleep interval of the IoT devices (Liang et al. 2013). Their approach allowed the node to keep in sleep mode until an event is triggered. Moreover, authors also proposed a strategy to maximize the sleep interval that helps in energy saving. In 2015, Kaur et al. (Kaur and Sood 2017) proposed a hierarchical layer based mechanism for enhancing the IoT energy efficiency. In their approach, the layers exchanged energy-related information between them for the prediction of sleep interval of sensors based upon their remaining battery level and previous usage history. Additionally, during their sleep mode, the allocated cloud resources to that sensor were re-provisioned to other sensors for better resource utilization. The cluster-based approach is one of the most followed approaches for resolving the energy consumption issue in IoT network and increasing the network lifetime. By using a suitable clustering approach, the average transmission distances of sensors can be reduced effectively. In 2017, Researchers also dealt with clustering of IoT devices and cluster heads selection for the responsibility of data transfer to the base station (Praveen Kumar Reddy and Rajasekhara Babu 2017). For cluster head selection, they proposed a combinatorial approach of gravitational search algorithm with artificial bee colony optimization. Parameters namely, Distance, energy, delay, load, and temperature of the IoT devices were considered in their approach. In 2015, Chang (Chang 2015) proposed a strategy where the residual energy and the center of gravity among the sensors were considered for the selection of appropriate cluster heads. In 2015, Shalli et al. (Rani et al. 2015) recommended a hierarchical network structure for deployment of IoT devices with high scalability feature. Moreover, authors introduced a concept of using cluster coordinators for balancing the load on both cluster heads and coordinators to ensure a better inter-cluster communication. Additionally, an energy efficient transmission algorithm for the implementation of an optimal model was also carried out in their work. In 2016, Antonino Orsino et al. (Orsino et al. 2016) stated that Long Term Evolution-Advanced (LTE-A) could play a vital role in IoT that can provide large infrastructure and a broad range of connectivity to the devices. But a large amount of data transfer consumes an enormous amount of energy. In this regard, they suggested to use network-assisted Device-to-Device (D2D) communications as a solution in which a single IoT device will act as an aggregator of all data coming from a cluster of devices. For that, they adopted a modulation and coding scheme for reducing the transmission power. In 2015, Bagula et al. (Bagula et al. 2015) suggested a role-based clustering model where every sensor played different roles in the cluster depending upon its residual energy at a different point in time. Additionally, the allotted role for a sensing node was also decided as per the service intensiveness of that node. A similar approach related to service and energy-aware clustering of sensing nodes were proposed by another group of researchers (Abidoye and Obagbuwa 2017). Due to the pervasiveness nature of IoT, it is necessary to integrate it with the cloud computing (Botta et al. 2016; Díaz et al. 2016). In 2015, Aazam et al. (Aazam et al. 2014; Aazam et al. 2015) highlighted different problems associated with IoT and introduced a term CoT (Cloud of Things) that use cloud computing mechanism for helping IoT to attain its goals and resolve the issues. In another approach, authors also proposed a smart gateway along with the fog computing based framework for providing better and fast service provisioning, data trimming and pre-processing (Aazam et al. 2014). Researchers also used various optimization algorithms in different ways for the improvement of energy-related issues in networks. In 2017, Song et al. (Song et al. 2017) proposed an approach in which by combining quantum particle swarm optimization (QPSO) with the improved non dominated sorting genetic algorithm (NSGA-II) an energy efficient IoT network can be formed. They considered a multi-objective optimization environment for confirming a better quality of service as well as an improved network lifetime. NSGA-II was used for the formulation of the multi-objective objective problem and QPSO was used for formation of optimum clusters. Authors suggested a device interaction aware clustering model that can work well for heterogeneous IoT systems where all the participating devices were configured with varied processing capabilities, energy, and bandwidth. In their approach, the cluster heads were elected by considering the residual energy along with the proximity to the devices. Researchers also proposed a genetic algorithm based energy efficient IoT clustering scheme and compared its performance with IEEE 802.15.4 protocol. They followed selection, fitness function, crossover, and mutation steps in their approach.

4 Proposed Method

4.1 System Model

The proposed architecture of the energy efficient smart healthcare system has been depicted in Fig. 1. In the proposed model, there are five entities: IoT devices, Micro Data Center, Data Analytic center, cloud server, and Application user.

a) IoT Devices: Internet of Things (IoT) refers to the electronic devices that are connected to the internet and capable of capturing or monitoring data and also intelligent enough to be active itself automatically while triggering of certain events. In healthcare, IoT devices have been introduced to patients in various forms like electrocardiograms, temperature monitors or blood glucose levels. It is also responsible for tracking other health information of patients continuously or at regular intervals.
b) Micro Data Center: Micro data center is a totally high enclosed unit which is responsible for temporary and frequent data processing at the edge of the network. MDCs are mainly designed for deployments in more remote locations like disaster-stricken or war-torn areas of the world (Majumdar et al. 2018). In the proposed system, each MDC is deployed in the fog layer and associated with a significant number of IoT devices or sensors of a geographical area. A Micro Data Center can be classified as either trigger based or periodic. The trigger based MDCs wait for a particular event to occur and transmit data only when an event is fired. On the other hand, periodic MDCs collect and transmit data at regular intervals or on arrival of a query.
c) Data Analytic Center: It acts as a data warehouse which is responsible for big data analysis such as, data mining, visualization, decision making, etc. In this healthcare system, the DAC gathers an enormous amount of health-related data from lots of IoT devices through edge network. Additionally, it processes further analysis upon it and stores it to the cloud server to provide valuable insights for future uses. It is also responsible for the clustering and cluster head selection process in the edge network. It fetches all the real-time characteristics of the MDC and performs the optimization to decide the cluster head for ensuring an energy efficient network.
d) Cloud server: It deals with the actual storage of electronic health records (EHR) in a secured manner. Moreover, a cloud server is responsible for in-depth analysis of the medical data received from different sources. It also maintains the authentication of data used by various users.
e) Application user: Users are those entities who wish to access a data or any kind of services from the cloud server. Authorized users are only permitted to access files from the cloud server. In the proposed system any doctor

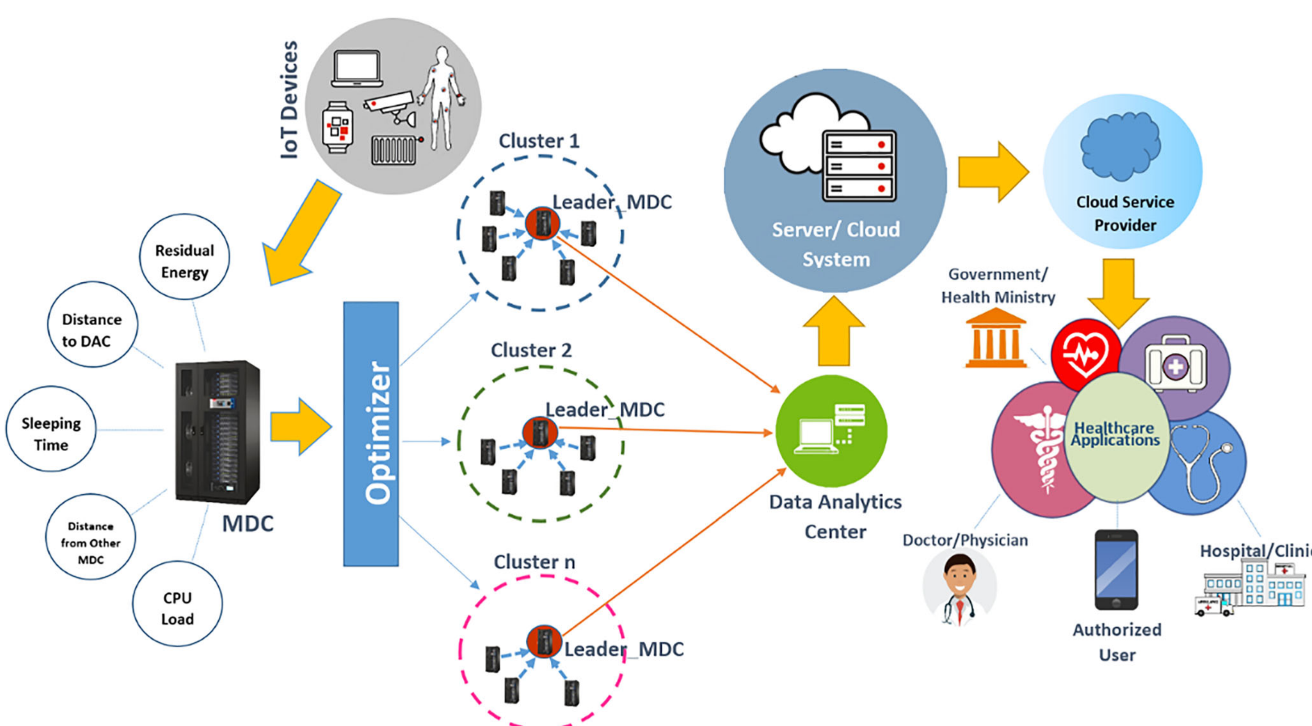


Fig. 1 Proposed framework

or health organization acts as a user and access the EHR through different healthcare applications.

4.2 Network Model

In this paper, for the simplification of the network model it is assumed that the network has the following properties:

a. All MDCs are distributed randomly in the geographic area.
b. Deployment of MDCs are static in the work environment. Once MDCs have been deployed, they work in the environment without movement.
c. The MDCs are homogeneous in that they have equal capabilities (initial energy, data processing, wireless communication).
d. All MDCs have power control capabilities and each node can change the power level and communicate with DAC directly.
e. DAC is fixed far from the sensor field and it is not energy constraint and it is placed at the center of the problem space.

As each edge device contains only limited power supply in the form of a battery cell, thus, the limited lifetime of the edge networks is a significant barrier that prevents the growth of edge networking. Furthermore, sending and receiving data in an edge network is considered as the most energy-consuming task of the nodes where the energy consumption is proportional to the distance between the sender and receiver (Kaur and Sood 2017). For example, closer to the receiver, the lower the power consumption and vice versa. The popular way to save device and network energy is to organize the network in the form of clusters and extending the lifetime of a network thereby. It comprises a cluster head that collects data from the cluster members present in its cluster and sends them the corresponding data analytic center. Hence, energy is saved by sending data to the cluster head instead of the data analytic center directly. However, in a cluster-based edge network, the network is only useful as long as all the edge devices within a cluster are acquiring and transmitting data, which is possible only as long as they have a source of power. Because of cost constraints, much known renewable sources of energy, such as solar or wind energy are used rarely. Besides, the edge devices are deployed over large areas and hostile environments, making it difficult to replenish or replace the batteries. Due to these reasons, prolonging the lifetime of an edge network is of utmost importance.

In order to further improve the network lifetime, the EO-μGA optimization based clustering approach has been implemented for the optimized clustering of the edge devices. The simulation results show that the EO-μGA model has a higher network lifetime concerning first cluster death and a lesser amount of transmission energy consumption per node as compared to various state of the art optimization algorithms. In this study, the lifetime of the network has been analyzed with respect to death time of first and the last cluster in the network.

4.3 Proposed EO-μGA Optimization

As the name signifies, the proposed EO-μGA optimization algorithm is a combination of the traditional extremal optimization and micro genetic algorithm. As discussed earlier, the μGA operates based on similar principles to the SGA but differs in the population size, use of elitism, crossover technique, and population regeneration in place of mutation. The smaller population size allows the μGA to optimize more quickly (Krishnakumar 1990) as each generation has fewer function evaluations than the SGA, and thus the μGA skips the mutation step. Despite having a smaller population size, the μGA requires the use of elitism to operate and continue to approach an optimal solution (Krishnakumar 1990). However, the small population size and lack of mutation lead to the μGA often drifting toward local maxima, which requires the algorithm to restart to escape a localized solution. In this regard, the extremal optimization can be used in place of the population generation of μGA.

In μGA, the population with the best fitness is directly moved for the next generation (elitism) and the others follow tournament selection strategy to make pairs and perform crossover operation to produce new offspring for the next generation. The proposed EO-μGA is also configured to deal with small number of populations in each generation as like as μGA but used ranking selection as selection criteria and uniform crossover mechanism. However, in EO-μGA, the elitism property has been slightly changed where rather than transferring the best population directly to the next generation, the offspring generated after performing crossover operation among the best four fittest population are transferred to the next generation. As a result, instead of moving the goodness of the best population only, the goodness of all the four fittest populations is inherited to their offspring. On the other hand, the extremal optimization is used here to replace the remaining six populations of lower fitness with newly generated random populations within the same search space. For maintaining enough diversity in the population more than half i.e. 60% of the population have been selected for EO and remaining 40% for the μGA. By using EO with μGA, a better and widely exploration of the search space is achieved. As a result, the set of offspring of the best populations along with the newly generated random populations can achieve an incredible diversity in the population. Consequently, the chances to get the desired solution is also increased, which leads to the EO-μGA being significantly faster than the traditional μGA and SGA. This speed enhancement is advantageous for real-time applications in which optimization must occur quickly. Moreover, the problem of μGA about drifting toward local maxima (premature convergence) due to initialization with an inferior set of populations is resolved by EO-μGA. The process is to be continued until the maximum number of generation has been reached or the convergence criteria has been satisfied.

4.4 EO-μGA Based Clustering

An optimization problem is the problem of finding the best solution or highest achievable performance from all feasible solutions concerning a set of prioritized criteria or constraints. Similarly, finding the best set of centroids within a search space that can make an optimized set of clusters of edge devices and guarantee energy efficiency in the edge network also comes under an optimization problem. In this regard, an optimization algorithm named EO-μGA has been proposed in this work to perform the task of finding the population having the best set of centroids that will form a suitable set of clusters. The detailed working principle of the EO-μGA as an optimization algorithm for finding the best centroids has been illustrated in the section.

In this work, the EO-μGA based energy efficient clustering strategy has been proposed to form the best set of clusters based upon the intended fitness function. The graphical representation of all the steps involved in this clustering strategy has been depicted in Fig.2. The whole process of clustering must undergo a series of repetitive optimization steps that have been listed in Algorithm 1 in detail.

In this algorithm, firstly, for a specific area, 'n' number of MDCs have been initialized randomly in different positions with different parametric values. Similarly, the position of the data analytic center has also been considered at the center of the defined area. The number of population has been set to be ten for each generation as the algorithm deals only in μ-scale of populations like μGA (Chakravarty et al. 2002). For the first generation, each population has been generated randomly where each population is comprised of 'm' centroid positions within the predefined region. The distance from each MDC to each centroid has been calculated and the required number of clusters have been formed for each population accordingly. The nearest neighbor method has been used here to make a distinct set of clusters to reduce the average transmission distances among MDCs. In this method, all micro data centers compute the distance from each centroid and join under the closer one to form a cluster. In this way, all the MDC's will come under.

Algorithm 1. Proposed EO-μGA for best clusters formation.

Input: Problem space, Population size (popsize), Generation number (max_gen), weight factors of OEC (w1….w5).
Output: Best population of a combination of 5 clusters which have equally good fitness.

1. Generate and fix the positions of 100 MDCs (mdc_1, mdc_m….mdc_{100}) and DAC (dac).
2. Assign the properties of the MDCs and calculate their distance from the base station.
   $$d(mdc_m, dac) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$
3. Generate initial population of *popsize* having positions of 5 different centroids (*cen1, cen2…cen5*). The *popsize* is in μ-scale.
4. While $gen < max\_gen$
   a. Calculation of real values from the population
      i. $$cen_{(i,j,x)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\x=latitude}} = (X_{min} + \frac{(X_{max}-X_{min})}{2^n-1} \times decode\,(n)_{i,j}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}} \quad (1)$$
      ii. $$cen_{(i,j,y)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\y=longitude}} = (Y_{min} + \frac{(Y_{max}-Y_{min})}{2^n-1} \times decode\,(n)_{i,j}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\5\le n\le 8}} \quad (2)$$
   b. Distance of each MDC from centroids
      i. $$d\_cen_{(i,j,k)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\1\le k\le tot_{mdc}}} = \sqrt{\left(cen_{(i,j,x)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\x=latitude}} - mdc_{(i,j,x)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\x=latitude}}\right)^2 + \left(cen_{(i,j,y)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\y=longitude}} - mdc_{(i,j,y)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize\\x=longitude}}\right)^2} \quad (3)$$
   c. Perform nearest neighbor clustering based on d_cen and generate clusters (c_1, c_p…c_5).
   d. Calculation of fitness of each MDC
      i. $$fitness(mdc_m)_{(i,j)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}} = \sum(w_{i,j} \times f_{i,j})\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}} \quad (4)$$
   e. Identify cluster head for each cluster
      i. $$CH(C_p)_{(i,j)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}} = best(fitness(mdc_m)_{(i,j)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}} \quad (5)$$
      Where, $\forall mdc_m \in C_p$
   f. Calculation of fitness of each cluster
      i. $$fitness(C_p)_{(i,j)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}} = \sum \frac{fitness(mdc_m)_{(i,j)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}}}{|C_p|} \quad (6)$$
      Where, $|C_p|: Number\ of\ members\ under\ p^{th} cluster$
      and $\forall mdc_m \in C_p$
   g. Identify the best population based on closeness proximity of cluster fitness.
      i. $$CP(C_p)_{(i,j)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}} = dev(fitness(C_p)_{(i,j)}\Big|_{\substack{1\le i\le gen\\1\le j\le popsize}}) \quad (7)$$
   h. Perform sorting of population based on $CP(C_p)$
   i. 40% of the population that gives best fitness will be copied to a mating pool for crossover
      i. Ranking selection
      ii. Uniform Crossover (crossover probability=0.5)
      iii. Formation of new children solution
   j. Perform extremal optimization
      i. The remaining worse 60% of the population will be regenerated randomly to widely search in that domain.
      ii. Formation of new children solution
5. After that, the whole population is club together to form the populations for $gen + 1$ generation.
6. End While
7. Find the global best solution
8. End

a cluster. Afterward, evaluate the fitness of every MDC with respect to the fitness function (Eq. (16)). Then the fittest MDCs within each cluster for that period have been identified as the corresponding cluster heads. After that, fitness of each cluster has been calculated by finding the mean fitness values of all the MDCs present in the respective clusters. Then the

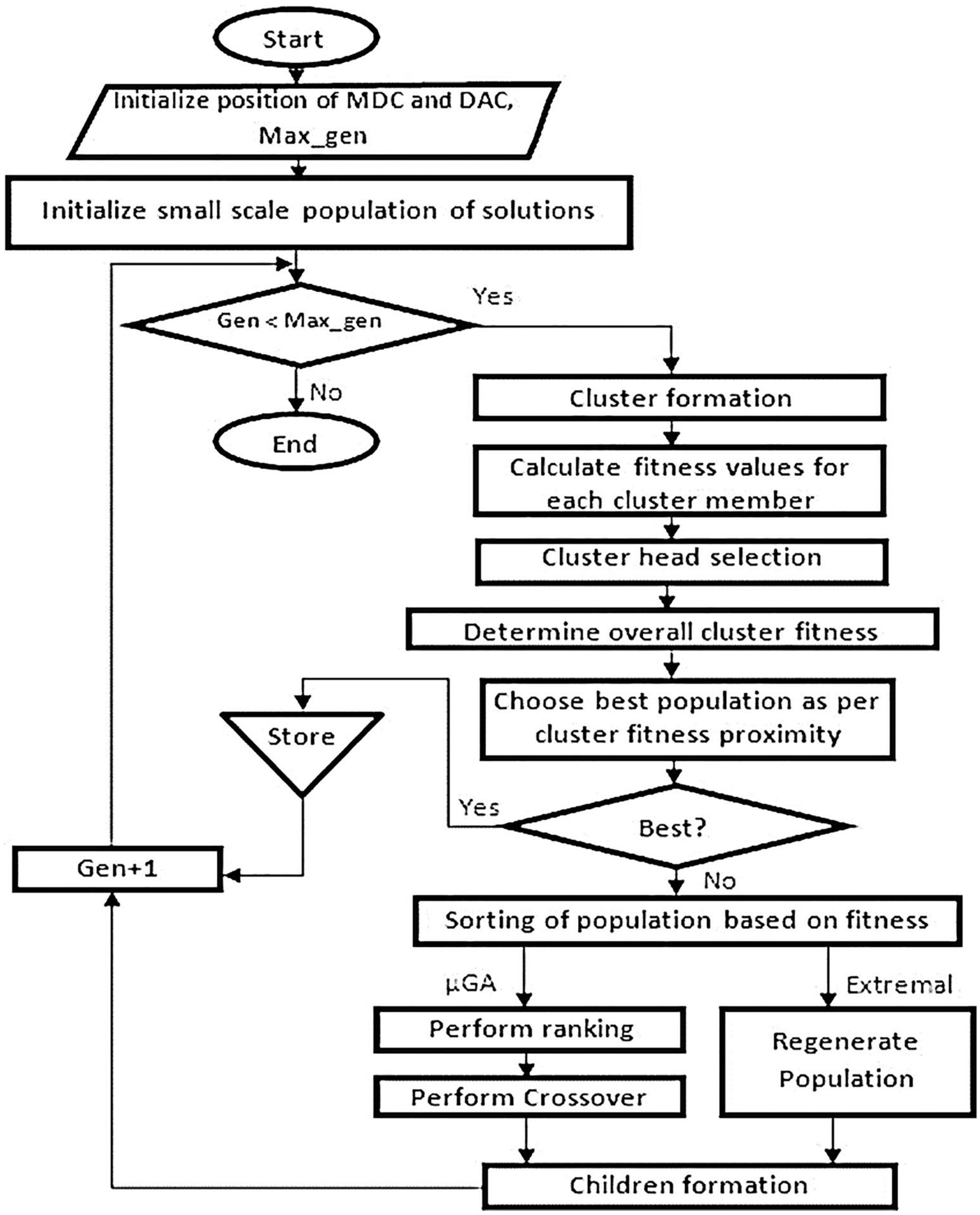


Fig. 2 Flowchart of proposed EO-μGA

difference between the minimum and maximum fitness values of clusters present within a population has been calculated and named as closeness proximity. Lesser cluster proximity value implies better energy efficiency since a smaller difference between cluster fitness confirms better balancing of clusters with respect to energy perspective. Similarly, the closeness proximity for each population has been identified. Subsequently, all the populations have been ranked as per their closeness proximity. After that, the best population is to be identified based on closeness proximity of cluster fitness. It means that the best population of a combination of 'm' clusters is to be chosen which have equally good fitness. If the newly found one is better than the previously stored population, then the new one will be replaced with the stored one and termed as the best population found so far. Otherwise, based on their ranks, the four fittest populations have been selected for the modified μGA operation, whereas the remaining six inferior populations have been selected for EO operation. In the μGA phase,

Table 1 Significance scale of criteria

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 Exhibit of Random Consistency Indices (RI) (Saaty 2005)

No. of evaluated Criteria (N)	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

the ranking selection has been applied and the uniform crossover operation among the selected population pairs have been performed. As a result, four new offspring have been introduced. The EO has been performed thereafter to generate new populations randomly to maintain population diversity. The resultant offspring from μGA and the newly created random populations from the EO club together to form the population for the next generation. This process continues until the maximum generation is reached or the final optimal best cluster combination arrives over all generations. The final optimal population has been stored for generating the final set of suitable clusters of MDC and corresponding cluster-heads. The necessary modules of this approach such as criteria weight generation and fitness function generation have been illustrated in detail in the consecutive sections.

4.4.1 Fitness Function Derivation

The next step is to calculate the fitness value of each individual in the clusters according to the proposed novel fitness function. Survivability of an individual depends upon its fitness value. Fitness value of each individual is calculated according to a fitness function. In our work, the fitness function consists of following five parameters or criteria:

a. Energy factor:

This factor specifies the remaining energy of a node n_i over the initial energy at the time of deployment.

Table 3 Weight determination of criteria

Criteria	f_{RE}	f_{IDC}	f_{DAC}	f_{TD}	f_{ST}
a) Pairwise comparison matrix for the criteria					
f_{RE}	1	5	5	6	7
f_{IDC}	0.2	1	1	3	5
f_{DAC}	0.2	1	1	2	4
f_{TD}	0.166667	0.333333	0.5	1	2
f_{ST}	0.142857	0.2	0.25	0.5	1

b) Result obtained from the AHP

Criteria	Weights (W)	λ_{max}, CI,RI	CR
f_{RE}	0.562763	Max. Eigen value	0.03999
f_{IDC}	0.170067	$\lambda_{max} = 5.178908$	
f_{DAC}	0.146832	CI = 0.044727	
f_{TD}	0.075185	RI = 1.12	
f_{ST}	0.045154		

$$f_{RE} = \frac{E_{curr}}{E_0} \tag{8}$$

Where E_{curr} = Current energy of MDC; E_0 = Initial energy of MDC.

a) Average Intra cluster distance:

This factor calculates the average distance between the remaining nodes of the cluster C_k from selected cluster member $n_{i.}$

$$f_{ICD} = \frac{\sum_{j\neq i; n_j\in C_k}^{|C_k|} d\left(n_i, n_j\right)}{|C_k|} \tag{9}$$

Where $|C_k|$ = Number of members in k^{th} cluster;

b. Average distance to cluster leader over DAC:

This is the factor specifies the ratio or goodness of distance from n_j to selected node n_i over distance from n_j to the DAC.

$$f_{DAC} = \frac{\sum_{j\neq i; n_j\in C_k}^{|C_k|} d\left(n_i, n_j\right)}{\sum_{j\neq i; n_j\in C_k}^{|C_k|} d\left(n_j, DAC\right)} \tag{10}$$

Where $|C_k|$ = Number of members in k^{th} cluster;

c. Average Sleeping Time:

This factor depends on the previous history related to sleeping intervals of a node. In the proposed approach, sleep interval of each MDC has been set on the basis of emergency cases or highly suspicious cases. In highly suspicious cases the sleeping time of an MDC will be less due to the emergence of continuous or regular data transmission to monitor the

Table 4 Simulation Parameters (Majumdar et al. 2019)

Properties	Values
Number of nodes/MDC	100
Number of clusters	5
Initial node energy (E_0)	20 kW
Idle state energy (E_{idle})	10^{-4} kW/C_L
Data aggregation (E_A)	10^{-5} kW/bit
Amplification energy (E_{amp})	10^{-8} kW/bit/m^2
Packet size from member MDC (k)	200 bit

Table 5 EO-µGA parameters

Properties	Values
Population	10
Converging Criteria in Accuracy	95%
Generation	120
Crossover Probability	0.5

health of the patient. Moreover, sleeping time of MDC can be adjusted by considering their sensing coverage and their distance from the leader-MDC or the DAC.

$$f_{ST} = \frac{\sum_{i=1}^{t} T_i}{t} \tag{11}$$

Where, T_i = Sleep interval (in seconds) for i^{th} time interval of a node; t = Total number of sleep intervals recorded for a node;

d. Computational Load:

This parameter specifies the computational load or CPU load at time t. It is measured in percentage.

$$f_{CL} = \frac{CL^t\,(n_i)}{100} \tag{12}$$

Criteria Weight Calculation The next step is to compute the weight or importance factors of each criterion. Since the most concerning aim is the energy efficiency of MDC, so, the energy factor parameter of the MDC is the most important factor among all. The average intra-cluster distance and the average distance to cluster leader over DAC are considered as the two most significant parameters in the proposed network because they save transmission time and network bandwidth. As a result of that, energy and the extra communication cost have been saved in a cloud environment. The remaining two parameters namely average sleeping time and computational load also play an essential role in the MDC network since lower computational load and higher sleep time will save the energy indirectly.

Herein, the weights of the criteria have been generated by pair-wise comparisons for each of the chosen criteria using the Analytic Hierarchy Process (AHP). AHP transforms the comparisons, which are most often empirical, into numerical values that are further processed and compared. The relative significance scale between two criteria as suggested by Saaty (Saaty 2005) is the most widely used. Attributing values that vary from 1 to 9, the scale determines the relative importance of a criterion when compared with another criterion, as shown Table 1. The pairwise comparison matrix has now been generated as shown in Table 3(a) by utilizing the significance scale listed in Table 1. The complete flow of tasks for weight generation through AHP is: initial group of criteria → comparison matrix for group of criteria → comparison matrix for group of criteria after normalization → eigenvector calculation → calculation of maximum eigenvalue (λ_{max}) → exhibit of random consistency indices (RI) as shown in Table 2 → the calculation of the consistency index (CI) using Eq. (13) ° ° the calculation of the consistency rate (CR) using Eq. (14) demonstrating the contribution or weights of each criterion to the goal defined. In order to verify whether the consistency index

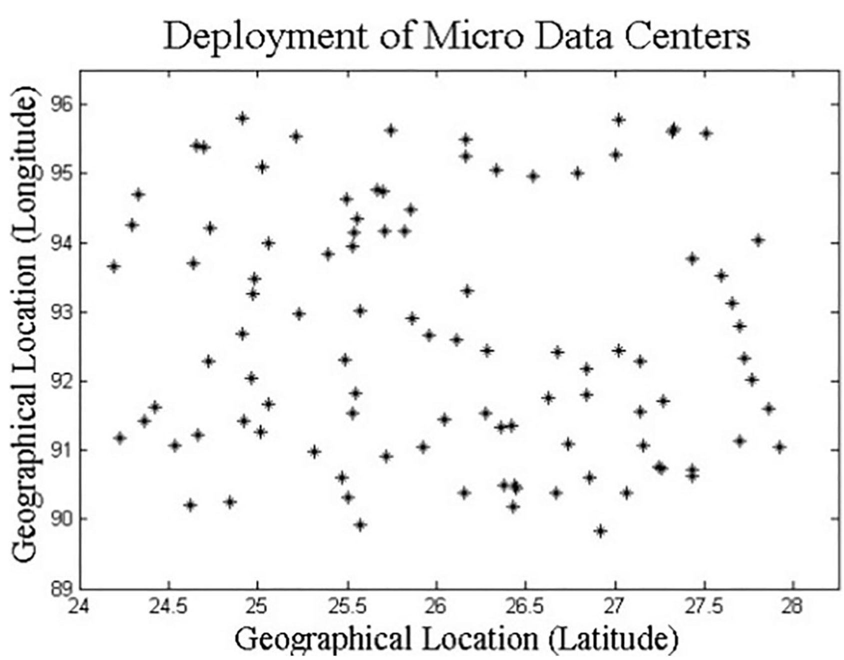


Fig. 3 Initial deployment of Micro data centers

Table 6 Comparison between the algorithms in terms of their best, worst, average and standard deviation

	PSO	HBPSO	SGA	WOA	DA	HWPSO	EO-μGA
Best	1.83E-03	1.31E-03	1.22E-03	6.23E-04	7.02E-04	5.40E-04	4.87E-04
Worst	3.27E-03	3.25E-03	3.94E-03	9.33E-04	9.14E-04	5.72E-04	5.14E-04
Average	2.54E-03	2.45E-03	1.94E-03	7.47E-04	7.72E-04	5.55E-04	5.00E-04
Std. Dev.	4.22E-04	6.03E-04	6.82E-04	9.04E-05	6.69E-05	1.08E-05	9.04E-06

(CI) is adequate, it is suggested that the consistency rate (CR), which is determined by the ratio between the consistency index and the random consistency index (RI) should be less than 10%. Table 3(b) represents the final weights of each criterion which has been calculated following the abovementioned process of the analytic hierarchy process (AHP) method. The obtained consistency rate is $0.03999 < 0.1 \sim 10\%$. Since the value is less than 10%, the weights can be considered to be consistent and can be used in further processing.

$$Consistency\ Index\ (CI) = \frac{\lambda_{max} - N}{N - 1} \tag{13}$$

Where N is the number of evaluated criteria.

$$Consistency\ Rate\ (CR) = \frac{CI}{RI} \tag{14}$$

Criteria Evaluation and Fitness Function Generation Since the criteria are different, it is not obvious that all the time the best solution obtained for one criterion will be desirable for other criteria also. To overcome this, the concept of multi-objective introduced and researchers have successfully used Overall Evaluation Criteria (OEC) method to achieve multi-objectives (Roy n.d.; Roy 2001; Singh et al. 2016; Wangikar et al. 2017). The OEC method has been used in this proposed work to satisfy multi-objective and formulate them into a single index (Singh et al. 2016). The data have been normalized and weighted accordingly. As mentioned earlier, AHP has been used to calculate the weights of criteria. To observe the combined effect of the five factors namely Energy factor, Average Intra cluster distance, Average distance to cluster leader over DAC, Average Sleeping Time and Computational Load, OEC analysis has been performed. Eq. (15) shows the formulation of OEC for the responses X and Y having weight percentages $W_x$and W_y respectively (Wangikar et al. 2017).

$$OEC = \left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) W_x + \left(1 - \frac{Y - Y_{min}}{Y_{max} - Y_{min}}\right) W_y \tag{15}$$

The quality characteristic (QC) for X is 'bigger is the best' (QC=B) and for Y is 'smaller is better' (QC=S). In this equation, the effect of all the criteria have been converted to bigger and for this, smaller criteria function have been subtracted from 1. After scaling the fitness function, we have fitness function as:

$$Fitness = W_1 f_{RE} + W_2(1 - f_{ICD}) + W_3(1 - f_{DAC}) + W_4(1 - f_{CL}) + W_5(1 - f_{ST}) \tag{16}$$

Our objective is to maximize the Fitness value. In other words, higher the fitness value, the better is the population.

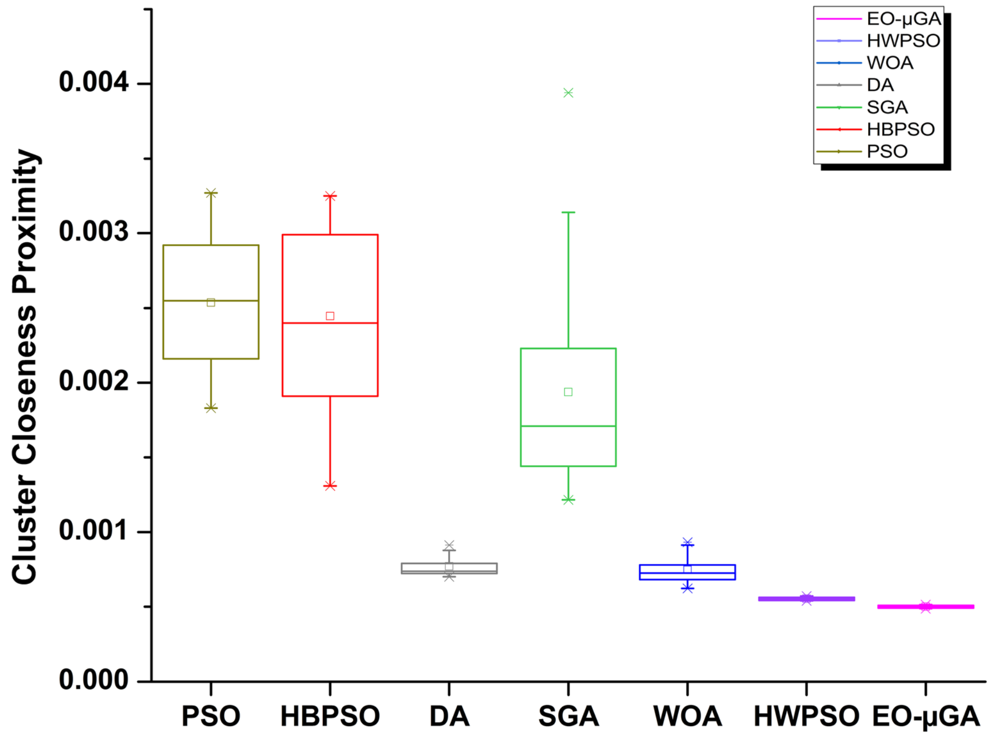
5 Simulation Results and Analysis

We performed extensive experiments on the proposed algorithm using MATLAB R2017b. As mentioned earlier, every member MDC transmit data to the cluster head and for that, they consume a certain amount of energy. Similarly, each leader-MDC in each cluster aggregate all the data coming from the other cluster members and transmit it to the DAC periodically. As a result, the leader-MDC, consume some extra energy due to aggregation as well as the bulk data transfer to the DAC situated at a distant place. Additionally, all the MDC consume some energy to execute its other computational needs. But, MDC does not enter into sleep mode while it is idle. The rate of energy consumed per transaction by leader-MDC or cluster head has been shown in Eq. (17) and same for the other cluster members has been shown in Eq. (18). All the network parameter values used for the simulation has been drawn in Table 4.

Table 7 Friedman's statistical test result

Algorithm	Mean Rank	Rank
PSO	6.50	7
HBPSO	6.17	6
SGA	5.32	5
WOA	3.35	3
DA	3.65	4
HWPSO	2.00	2
EO-μGA	1.05	1

Fig. 4 Box plot for 20 number of runs



Energy loss for cluster head in each transmission:

$$\left.\begin{array}{c} E_{CH(i)_{loss}} = E_{idle}+E_A+t\,E_{amp} \\ \hline t=(|C_i|-1)\end{array}\right\} \frac{Where, CH(i)\in C_i\ and}{|C_i| = number\ of\ nodes\ in\ i^{th} cluster.} \tag{17}$$

Energy loss for cluster members in each transmission:

$$\left. E_{CM(i)_{loss}} = E_{idle}+E_{amp} \right\} \ Where, CM(i)\in C_i \tag{18}$$

For observing the convergence rate and other measures in cluster formation, a performance based comparative analysis has been performed between EO-μGA and some high performing state of the art optimization algorithms namely Particle Swarm Optimization (PSO) (Kennedy and Eberhart 1995), Whale Optimization Algorithm (WOA) (Mirjalili and Lewis 2016), Human Behavior based PSO (HBPSO) (Hao et al. 2014), Simple Genetic Algorithm (SGA) (Holland 1992), Dragonfly Algorithm (DA) (Mirjalili 2016), and Hybrid Whale Particle Swarm optimization (HWPSO) (Majumdar et al. 2019; Laskar et al. 2019) etc. These algorithms demonstrated better performance when used in case of benchmark functions and is thus used for comparison with EO-μGA. Table 5 lists the values of the parameters considered during the simulation of EO-μGA. The simulations of

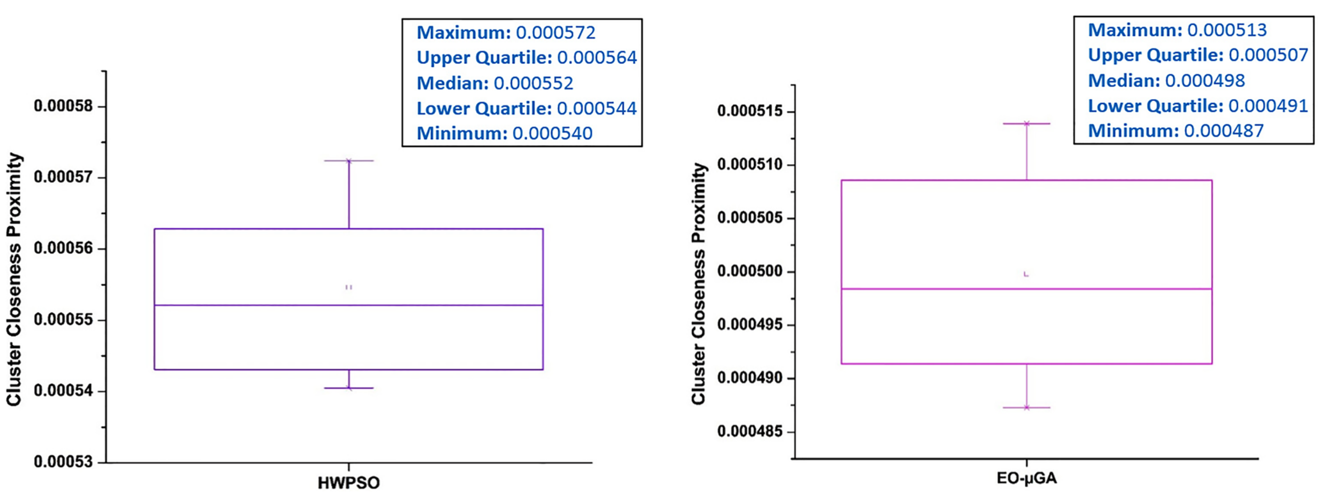


Fig. 5 Box plot of HWPSO and EO-μGA for 20 number of runs

other algorithms have been conducted against the same number of population and the maximum iteration limit. The initial deployment of MDCs has been depicted in Fig. 3 and the same has also been considered for the simulation of all the optimization algorithms. Table 6 shows the comparative analysis of the algorithms in terms of their best, worst, average and standard deviation for 20 number of runs. From the results obtained it has been observed that the EO-μGA is more consistent in terms of a lower standard deviation when compared with other state of art algorithms.

For validating the results obtained by the algorithms, Friedman statistical test has been performed. It is a non-parametric test used for ranking algorithms based on performance (Majumdar et al. 2019; Laskar et al. 2019). In the Friedman's test, the best performing algorithm has lowest mean rank while the worst performing algorithm is ranked highest. The results for the Friedman's test for the problem is shown in Table 7. It can be seen that the EO-μGA outperforms the state of art algorithm with a mean rank of 1.05, which further validates the result obtained. Figure 4 shows the box plot for all the considered optimization based clustering algorithms as per the statistical data. From the box plot statistical analysis it has been observed that EO-μGA and HWPSO are more consistent in terms of a lower standard deviation when compared with other state of art algorithms. The detailed box plot analysis for HWPSO and EO-μGA have been represented in Fig. 5. As seen from the figure, the optimum values obtained by EO-μGA lie close to each other having a low standard deviation at approximately half of the data set.

The convergence point analysis for all the above mentioned algorithms has also been conducted. Figure 6 represents the detailed graphical overview for finding the convergence point in case of all the above mentioned algorithms. In the case of PSO, it has been found stagnant at a cluster closeness proximity of 0.0018 from the iteration number 226 onwards. Whereas, in case of HBPSO it has been found stagnant at 0.0013 from the iteration number 175 onwards. HBPSO outperforms the basic PSO in better convergence speed and the cluster closeness proximity. The similar analysis for SGA (with population = 100, crossover probability = 0.5 and mutation probability = 0.1) has also been performed and found stagnant at 0.0012 from the iteration number 213 onwards. Moreover, in case of DA, it has been found stagnant at 0.0007 from the iteration number 183 onwards. For WOA, it has been found stagnant at 0.00067 from the iteration number 170 onwards. Clearly, WOA performs better with very less cluster closeness proximity value even at less number of iteration as compared to the HBPSO and SGA and DA. Whereas, HWPSO has been found stagnant at 0.00054 from the iteration number 41 onwards. Coincidently, EO-μGA has also been found stagnant from the iteration number 41 onwards but with a lower cluster closeness proximity of 0.00046. Hence, clearly EO-μGA yields better result in faster convergence with better cluster closeness proximity than the other four algorithms.

Moreover, an analysis to observe the changes in average residual energy of each cluster with respect to the number of data transmission process for all the optimization

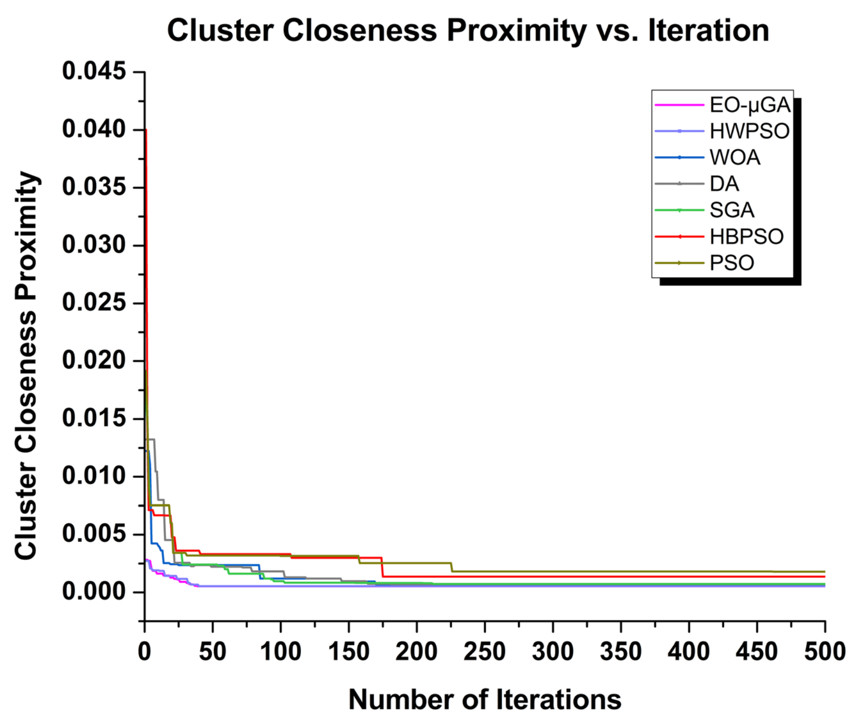


Fig. 6 Changes in cluster closeness proximity with the number of iteration

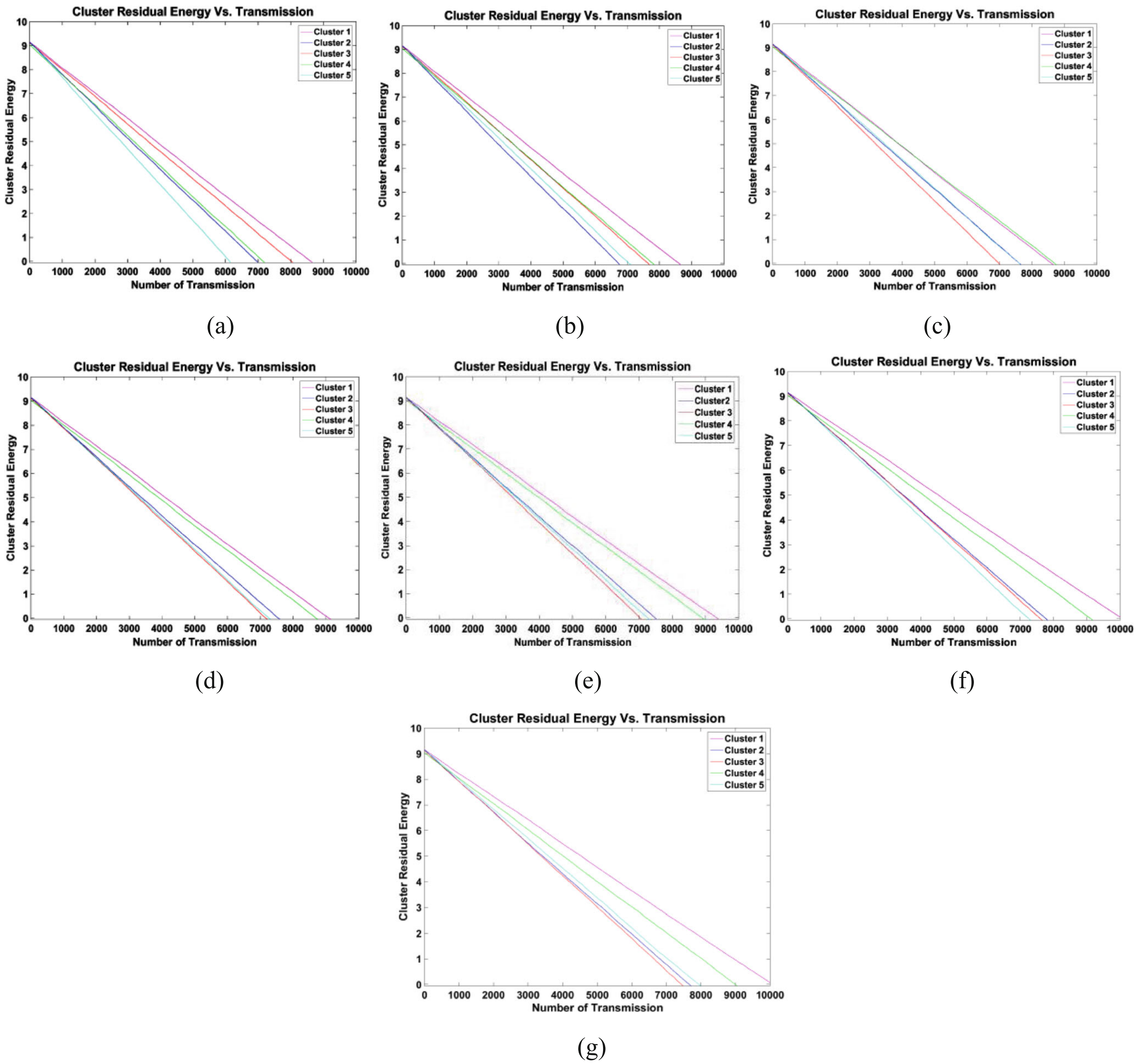


Fig. 7 Clusters residual energy in each transmission in case of (**a**) PSO (**b**) HBPSO (**c**) SGA (**d**) WOA (**e**) DA and (**f**) HWPSO (**g**) EO-μGA

algorithms (up to 10,000 transmissions) has been conducted. Figure 7(a)-(g) illustrates the clusters residual energy in each transmission for all the aforementioned algorithms. In case of PSO, after transmission number 6184 cluster-5 dies first. For HBPSO, it has been found that after the transmission number 6889 cluster-2 dies first. Similarly, in case of SGA cluster-3 dies first after transmission number 7014. It has also been noticed that in case of WOA cluster-3 dies first after transmission number 7203. For DA, after transmission number 7099 cluster-3 dies first. In case of HWPSO cluster-5 dies first after transmission number 7322. Moreover, for EO-μGA cluster-3 dies fast after transmission number 7503. Besides, it can also be noticed that in case of EO-μGA and HWPSO all the clusters sustain for a long time as compared to the others. From this analysis, it has been clearly perceived that the proposed EO-μGA outperform the other algorithms in the average network lifetime which is the actual signature requirement for an e-Healthcare system.

Since the performance of the HWPSO and EO-μGA based clustering was found close enough to each other so a comparison between these two in terms of network lifetime has also been observed. The optimized set of clusters in case of HWPSO and EO-μGA based clustering approach with their corresponding centroids and cluster heads are shown in Fig. 8(a) and 8(b) respectively. Whereas

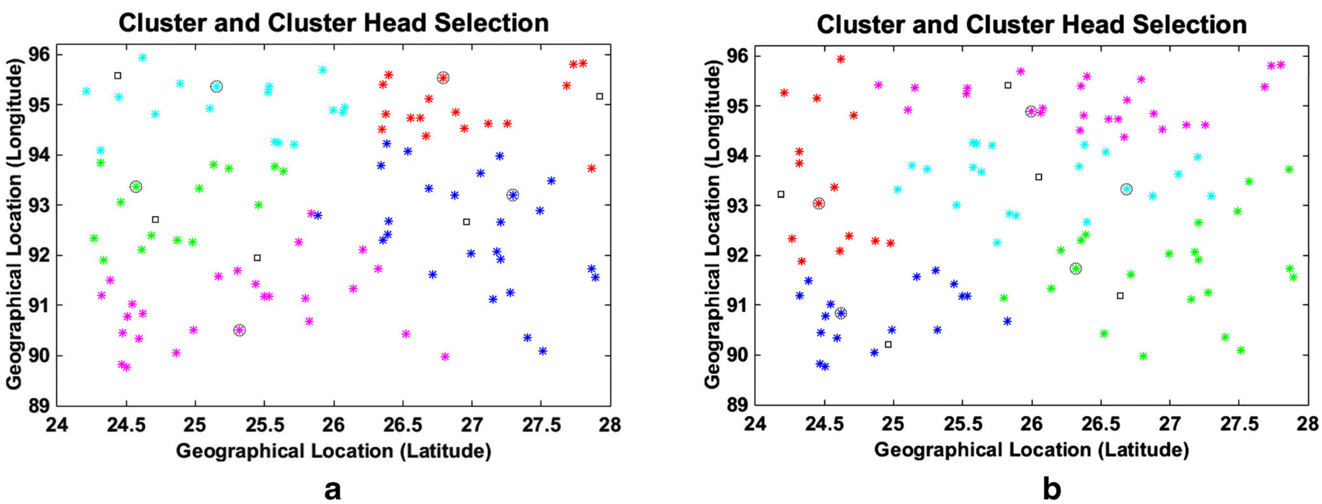


Fig. 8 Initial MDC clustering using centroids and cluster head selection in case of (**a**) HWPSO (**b**) EO-μGA

Fig. 9(a) and 9(b) depict the position of newly appointed cluster heads at transmission number 7322 and 7503 for the HWPSO and EO-μGA based clustering approach respectively. The centroids have been shown as square shaped icon whereas the cluster heads have been shown as the encircled star. From this analysis it can be resembled the fact that even at 7503 number of iteration the EO-μGA performs effectively to generate the set of clusters which have an equally good cluster closeness proximity.

6 Conclusions

Due to the technological advancements, it becomes much easier and effective to monitor, and diagnose many infectious diseases throughout various sensors and devices that help health sectors in taking necessary preventive measures. In this paper, a comprehensive framework for advanced e-Health monitoring system configured with a set of edge devices has been proposed. Moreover, the proposed EO-μGA algorithm provides a new perspective to measure the network lifetime which is much suitable for the online systems like e-Healthcare due to its light weight and faster convergence nature. Additionally, the proposed fitness function also claims that the longevity of a network should not be evaluated only based on the energy on the devices, but also other important parameters related to distance and computational status should also be taken under consideration. This system also confirms the formation of an efficient cluster-based e-Healthcare network where all the formed clusters configured with fog layer edge devices will have almost equally good in every respect that in turn confirms an organized energy consumption and better e-Healthcare network lifetime.

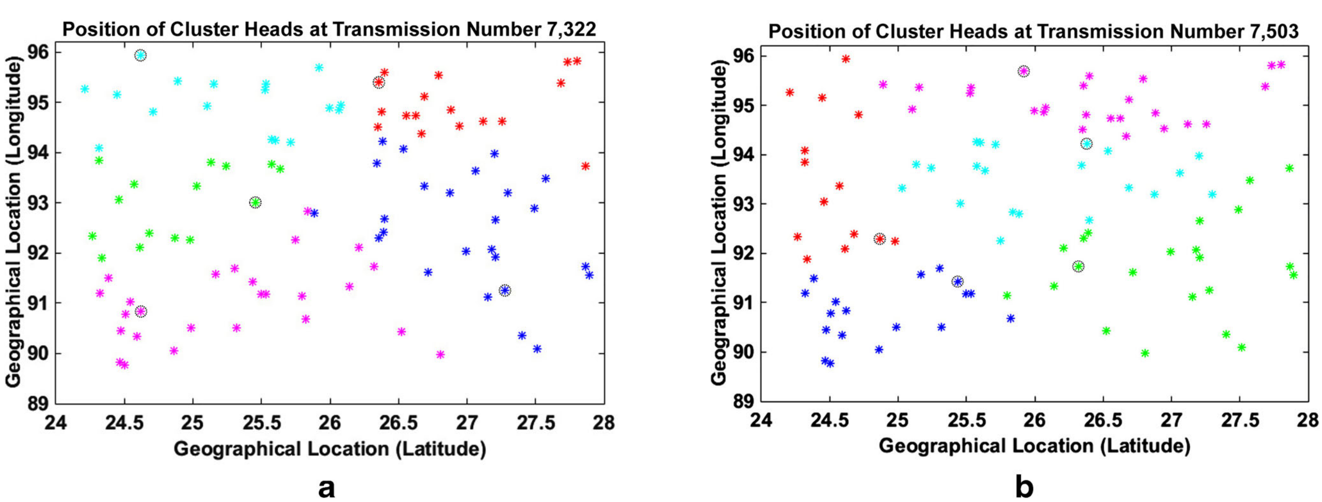


Fig. 9 Position of newly appointed cluster heads at (**a**) 7322 number of transmission in case of HWPSO (**b**) 7503 number of transmission in case of EO-μGA

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