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Optimized LEACH-based Energy Efficient Protocol for M2M Communications in Green IoT: Development of New Hybrid Algorithm

[1] Umakant L Tupe, [2] Dr.Sonali Kadam, [3] Dr.Parikshit N Mahalle

[1] Research Scholar, Department of Computer Engineering, Marathwada Mitramandal's Institute of Technology, Lohgaon, Pune, India
[2] Associate Professor, Bharati Vidyapith's College of Engineering for Women, Pune, India
[3] HOD & Professor, Department of Computer Engineering, SKNCOE, Pune, India
Email: [1] umakant.tupe@gmail.com, [2] kadamsonali@rediffmail.com, [3] aalborg.pnm@gmail.com

***Abstract---* Internet of Things (IoT) is a promising model, which has attained more demand in research field nowadays. The multiple sophisticated and well-performing devices integrated with IoT system require more energy. Hence, the problem of energy consumption in IoT network is considered as the significant research area. Moreover, Green IoT takes the role of minimizing energy consumption in IoT devices thus achieving sustainable environment for IoT systems. The main intention of this proposal is to develop an energy-efficient protocol for M2M communication in Green IoT using a clustering process incorporated with hybrid meta-heuristic algorithm. The energy-efficient Green IoT is developed by the proposed LEACH protocol, aiming to diminish the power consumption at different levels. The main objective of the proposed protocol is to minimize the energy consumption of M2M communication, by minimizing the distance between the devices, and delay while transmitting data with the development of cluster head selection. In order to attain this objective, the proposed LEACH protocol utilizes the hybrid meta-heuristic algorithm that merges the beneficial concepts of both Whale Optimization Algorithm (WOA), and Deer Hunting Optimization Algorithm (DHOA), and the hybrid algorithm is termed as Whale-based DHOA (W-DHOA). The combination of these two algorithms in LEACH protocol performs well in cluster head selection to minimize the energy consumption, thus maximizing the network lifetime, which leads to frame an energy efficient Green IoT.**

***Keywords---* Internet of Things; Green IoT; Energy Efficiency; LEACH Protocol; Whale Optimization Algorithm; Deer Hunting Optimization Algorithm; Whale-based Deer Hunting Optimization Algorithm**

NOMENCLATURE

Abbreviations	Descriptions
IoT	Internet of Things
M2M	Machine-to-Machine
LEACH	Low Energy Adaptive Clustering Hierarchy
WOA	Whale Optimization Algorithm
DHOA	Deer Hunting Optimization Algorithm
W-DHOA	Whale-based DHOA
RFID	Radio Frequency Identification
SEP	Stable Election Protocol
WSN	Wireless Sensor Network
LTE-A	Long Term Evolution-Advanced
Z-SEP	Zonal-Stable Election Protocol
AKA	Authentication and Key Agreement
MTCD	Machine-Type Communication Device
SEGB	Security Enhanced Group Based
MTCG	Machine-Type Communication Gateway
MEC	Mobile Edge Computing
QoS	Quality of Service
eSIM	embedded-SIM
POMDP	Partially Observable Markov Decision Process
SDN	Software-Defined Networking
KFS/KBS	Key Forward/Backward Secrecy
H2H	Human-to-Human
TDMA	Time Division Multiple Access
AVISPA	Automated Internet Security Protocols and Applications
FF	Fire Fly
GWO	Grey Wolf Optimization

I. INTRODUCTION

IoT was initially introduced by Kevin Ashton in 1998, who defines “The IoT has the ability to change the world as if the internet has done or even more so”. IoT is taken as one of the fascinating applications, which permits the things and users to be associated in any place, any time, with anything and anyone, through any service and link. IoT involves huge development of network utilization and the count of nodes in the future [23]. It is mandatory to decrease the resources for applying whole network elements, and the usage of energy for operation. Consumption of energy is becoming a key objective to attain a Green IoT consistency and smart world application [9] [24]. IoT must be described by energy efficiency for decreasing the effects of greenhouse and carbon dioxide emission of sensors, applications, services, and devices in order to have a comfortable smart world [10] [11] [12].

Many technologies towards Green IoT must incorporate “green cloud computing network, green RFID tags, and green sensing network”. RFID is a very minute device, which consists of various very little tag readers, and RFID tags. RFID tags are able to keep the data about the objects to which the tags are associated. Generally, the diffusion range of RFID devices is only some meters. Passive and active tags are the two types of RFID tags. The passive tags do not have its individual battery, whereas the active tags include the batteries for continuous diffusion of their individual signal. The passive tags require the energy produced from the reader signal in the place of its individual battery [22]. Many research accomplishments have been performed for attaining the objective of green RFID. Along with that, a green WSN is the other major technology to allow green IoT [13] [25]. WSN consists of the fabulous count of sensor nodes via inadequate storage capacity and power. In order to attain green WSN, various methods need to be implemented.

Though several energy-efficient protocols were introduced, the protocols are adaptable only in heterogeneity with few battery sensors [14] [15] [16]. IoT atmosphere needs thoughts of the difference of the heterogeneous nodes concerning both energy consumption as well as energy content. In WSN [17], LEACH protocol [18] was generally utilized protocol and several improved versions were presented [19]. Moreover, LEACH is introduced for compacting with uniform sensor nodes as it assumes that the whole number of nodes will have equal energy. Here, SEP is offered as the heterogeneous aware protocol [20], which selects the cluster-heads by the possibilities of election and are weighted by the node's primary energy corresponding to the nodes of other networks. In order to increase the performance of IoT network, ZEP offers a zonal heterogeneous protocol that has been very closer to the IoT multi-region environment by not using this heterogeneity. Z-SEP segregates network field using the location of base station close to the normal nodes, which transfers the information straight to the base station. Conversely, the advanced nodes that are taken away from the BS utilize clustering approaches in diffusion to base station to conserve energy [21]. Moreover, there are several hurdles and challenges, which requires to be noted in energy-efficient Green IoT. Some of the conventional challenges are complexity reduction of the green IoT infrastructure, energy efficiency in IoT, and reliability of green IoT with energy consumption models for acquiring an acceptable performance.

The main contribution of this paper is discussed as follows.

- To synthetically create an IoT network in which the energy efficient clustering protocols have to be implemented with numerous IoT devices.
- LEACH is the well-known distributed cluster-based routing protocols in WSNs. It considerably relies on cluster heads rather than normal nodes for communicating to the base station. Owing to this, there results in generating robustness problems like cluster head failure may come about. Moreover, it does not work well with the applications that need huge area coverage along with multi-hop inter-cluster communication. Hence, the third objective is to implement a hybrid optimization algorithm W-DHOAN with the merging of two renowned optimization algorithms like WOA and DHOA that is well suitable for developing energy efficient Green IoT for improving LEACH concept.
- To frame a multi-objective function to build up energy efficient protocol for Green IoT with the intention of solving several existing problem in W-DHOA linked LEACH-based clustering protocol.
- To validate the performance of optimized LEACH protocol by comparing it over conventional models through the analysis pertain to the number of alive nodes, normalized energy, distance between the nodes etc.

The entire paper is designed in the following manner: Section II specifies the literature review and the features and challenges of the existing energy efficient protocols for m2m communication in IoT devices. Section III describes the cluster head selection in Green IoT: a multi-objective function basis. Section IV describes the hybridization of deer hunting and whale optimization algorithm for energy efficient Green IoT. The results and discussions of the paper is discussed in Section V. At last, the conclusions of the entire paper are given in Section VI.

II. LITERATURE REVIEW

A. Related Works

In 2018, Li *et al*. [1] have introduced a power allocation method using Lagrange multipliers approach on LTE-A cellular uplink for huge M2M communication. The suggested model has reduced the signaling overheads by authorizing MTCD to get permission to enter the Base Station using a MTCG, which transferred the data to the base station by gathering the information from the collection of M2M devices. The main intention of the developed system was to improvise the entire energy effectiveness of a cluster of M2M devices, whereas the time delay was fulfilled by collaborating the power diffusion of the MTCG and MTCDs. Therefore, the results of the recommended approach have verified that it was superior to the conventional approach.

In 2018, Sadek [2] has suggested an effective “hybrid energy aware clustering communication protocol” for Green IoT network computing Hy-IoT. The choice of effective cluster-head has increased the usage of the energy contents of the nodes as well as simultaneously improved the network’s lifetime and the diffusion rate of packets to the BS. Hy-IoT employed various weighted selection prospects for choosing a cluster-head depending on the heterogeneity level of the area. The performance validation has shown that the Hy-IoT extends the life time of network and improved the throughput, when compared with LEACH, Z-SEP, and SEP. Moreover, Hy-IoT produced extension of the network life time, and along with that, the average throughput was increased on the basis of heterogeneity level.

In 2019, Li *et al*. [3] have developed MEC methodology in virtualized cellular networks with M2M communications, to reduce the usage of energy and the determined resource allocation was optimized and increase the computing ability. In addition, the physical network was virtualized into many virtual networks based on the various functions and QoS prerequisites, and later every MTCD chooses the equivalent virtual network in order to permit through eSIM technology. In the meantime, the MTCDs random process was designed as a POMDP to reduce the expenses that include both the execution time and energy utilization of measuring tasks. In order to simplify the structure of the network incorporation, SDN was developed to handle the different protocols and benchmarks in the networks. Therefore, the comprehensive simulation results with distinct system parameters have shown that the suggested technique was increased its system performance when compared over traditional methods.

In 2018, Parne *et al*. [4] have offered the SEGB AKA protocol in an IoT enabled LTE/LTE-A network for M2M communication. The suggested protocol has resolved the individual key issue in the process of verification and attained the KFS/KBS. Moreover, it overcomes the risk of signaling obstruction and elevated usage of bandwidth. By using AVISPA tool, the appropriate security examination of the suggested protocol was considered. The analysis has shown that the protocol attained the security goals and was independent from different attacks. Furthermore, the suggested protocol’s performance was examined over conventional group based AKA protocols.

In 2018, Behera *et al*. [5] have improved the existing LEACH clustering protocol by establishing a threshold boundary for the selection of cluster head through simultaneous shifting of the power level among the nodes. The suggested LEACH protocol gave the best outcome when compared over conventional LEACH protocol with 67% improvement in throughput and increasing the number of active nodes to 1750 rounds that were employed for enhancing the lifespan of WSN. Hence, the performance of the recommended algorithm was seemed to be better, while considering the network’s lifetime and the stability period in distinct synopsis of an area, energy and node density.

In 2018, Li *et al*. [6] have proposed a protocol named three-factor user authentication protocol for WSN for detaching the flaws of earlier protocols. The safety of the developed protocol was examined and the functionality, performance, and protection of the presented protocol was compared over different corresponding protocols. Hence, the simulation and the comparison outcomes by NS-3 has revealed that the developed model was energy-efficient and strong for IoT networks.

In 2019, Renuka *et al*. [7] have presented a secure and effective authentication model in IoT enabled Cyber-Physical Systems for M2M communication. The suggested model permitted multiple pair of entities in this communication for mutual authentication and granting on a session key to effective and secure communication. The validation procedure doesn't include the M2M service provider, and therefore eradicates the weight of supervision of the verification process of large scale devices on the rim of the network. Moreover, the developed model asked the user to carry only one secret key given by the service provider, so that the user was able to wander in the whole network at random and authenticate to any of the gateways present in the area. Authentication was attained by some symmetric key encryptions, and hash invocations. Finally, the suggested model was examined by BAN logic that was extensively adopted as a framework to evaluate the authentication protocols and along with that ProVerif was utilized, and the calculated effectiveness was compared over few newly introduced models.

In 2018 Alqahtani [8] has developed a hybrid preemptive or non-preemptive restart priority system, which was capable of holding the heterogeneity requests of M2M services during the absorption of LTE networks. The relations among H2H and M2M were preemptive in the suggested approach while M2M and M2M were non-preemptive. Moreover, the classification of M2M traffic was done into a number of classes regarding the sensitivity delay of every traffic services. The systematic approach was introduced to calculate the performance delay of the suggested approach. Further, the recommended system was compared based on the simulation results with two conventional resource allocation models. Hence, the results have proven that the suggested model gave the best performance, where the extensive diffusion time was less.

B. Review

Though there are various energy efficient protocols to enhance Green IoT, yet it is still in initial phase. Some of the advantages and disadvantages of the conventional protocols are defined in Table 1. Among them, Lagrange multipliers method [1] permits the optimization to be resolved without explicit parameterization regarding restrictions, and has high performance. Still, it deals with inequality constraints. Weighted Probability [2] increases the lifetime of the network, and has high throughput. But, it is computationally expensive, and increases the complexity. MDP [3] requires less time to compute, and adaptive to changing, anonymous characteristics of the environment. Yet, it may take longer to converge due to bootstrapping. Binary Tree [4] used to represent hierarchies, and has high efficiency. Though, it is having a defect like it is very complex. Modified LEACH [5] has best performance, and has better system life time and energy consumption. Yet, there are some defects like if cluster head dies due to any reason, then the cluster head becomes useless as the collected information would never reach its BS, and it doesn't provide any information concerning the cluster heads count present in the network. Fuzzy Extractor [6] has less complexity, as well as less computational cost. Though, it is computationally infeasible to identify two various inputs that hash to the same value. BAN Logic [7] has high efficiency, and it is a good proof of correctness based on the assumptions. However, there are few disadvantages like final beliefs can be believed only if all original assumptions hold true, and doesn't account for improper encryption. Preemptive/Non-preemptive service strategy [8] has high throughput, and good response for the highest priority processes. But, it has a conflict like starvation may be possible for the longer processes. Hence, the future enhancements can refer to the above-specified conflicts to improve the researches in a better way for efficiently developing an energy-efficient Green IoT.Features and challenges of existing energy efficient protocols for M2M communication in IoT devices.

Author [citation]	Methodology	Features	Challenges
Li *et al.* [1]	Lagrange multipliers method	• Permits the optimization to be resolved without explicit parameterization regarding restrictions. • Has high performance.	• Deals with inequality constraints.
Sadek [2]	Weighted Probability	• Increases the lifetime of the network. • Has high throughput.	• It is computationally expensive. • It increases the complexity.
Li *et al.* [3]	Markov decision process	• Requires less time to compute. • Adaptive to changing, anonymous characteristics of the environment.	• It may take longer to converge due to bootstrapping.

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Parne *et al.* [4]	Binary tree method	• Used to represent hierarchies. • Has high efficiency.	• It is very complex.
Behera *et al.* [5]	Modified Low-Energy Adaptive Clustering Hierarchy protocol	• Better system life time and energy consumption. • Has best performance.	• If cluster head dies due to any reason, then the cluster head becomes useless as the collected information would never reach its BS. • Doesn't provide any information concerning the cluster heads count present in the network.
Li *et al.* [6]	Fuzzy Extractor	• Has less complexity. • Computationally less cost.	• It is computationally infeasible to identify two various inputs that hash to the same value.
Renuka *et al.* [7]	BAN logic	• Has high efficiency. • It is a good proof of correctness based on the assumptions.	• Final beliefs can be believed only if all original assumptions hold true. • It doesn't account for improper encryption.
Alqahtani [8]	Preemptive/nonpreemptive service strategy	• Throughput is high. • Good response for the highest priority processes.	• Starvation may be possible for the longer processes.

III. CLUSTER HEAD SELECTION IN GREEN IOT: A MULTI-OBJECTIVE FUNCTION BASIS

A. *System Model*

As there is a quick growth in population density in urban regions, it needs the latest designs with appropriate services in order to satisfy the needs of the city residents. Therefore, the modern versions in communication technologies like IoT have been requested for offering a model to develop smart cities [28]. Here, the environmental monitoring scheme employs WSN as an essential part of IoT. For the energy efficient IoT, assume a network that involves multiple count of nodes or devices.

Consider a Green IoT, in which the C_N number of clusters is considered. The term C_i indicates the cluster, where $i = 1,2,\cdots,C_N$. The normal node in any of the cluster is denoted as S_u, and the cluster head in each cluster is denoted as ch_i. While accomplishing the Green IoT through cluster head selection approach, the constraints like energy consumption, distance between the nodes, and the transmission delay is taken into concern. The architectural representation of the cluster head selection in WSN basis for Green IoT is shown in Fig. 1.

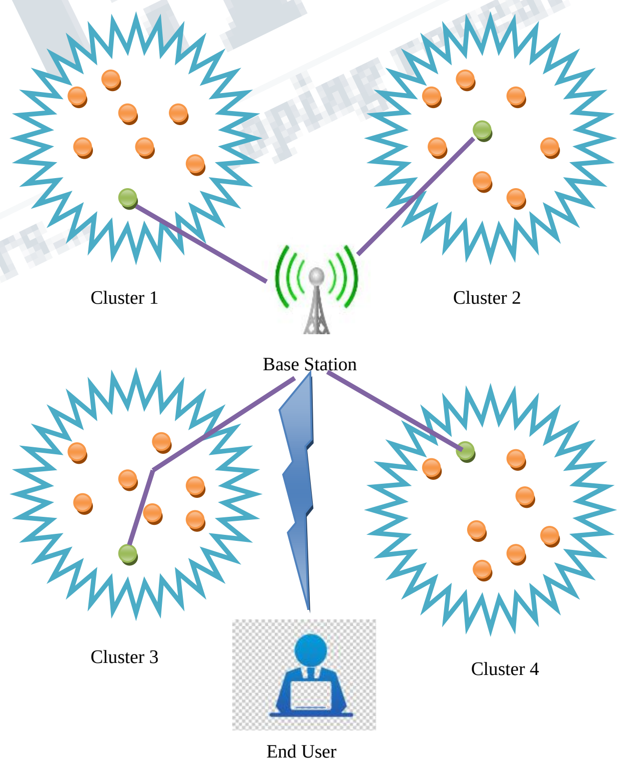

Fig.1 View of cluster head selection

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According to Fig. 1, the nodes are clustered into four distinct clusters or rooms. In each room, there are eight sensor nodes, in which only one node has the ability to become the cluster head in each instant of time. The base station or sink node gathers the data from the cluster heads present in each room and that information is combined and sent to the end user. Few sensible assumptions are taken into consideration for system modelling that is given below.

1. The nodes are homogeneous and static with the starting energy i.e., 0.5J and are dispersed in rooms for screening the variables like luminosity, sound, humidity, and sound.
2. In the centre of the network, the base station is set and installed.
3. The nodes are placed at random and transferred its data occasionally.
4. In each room, there is a cluster head, which communicates with the sink node in either single hop or multi-hop communication.
5. The sink node receives the information from each cluster head from all the rooms and transmitted.

B. Objective Model

Fig. 2 depicts the diagrammatic view of the proposed clustering approach in Green IoT. The objective models concerns for developed cluster head selection involves the constraints like energy, distance and delay. Here, C_N number of clusters is taken. The nodes from each cluster are assigned as the solution to the hybrid meta-heuristic algorithm taken as the key contribution. The proposed W-DHOA takes these solutions as input and follows the main steps like initialization, proposed fitness evaluation, update based on DHOA and random whale and termination. The parameters like energy, distance and delay is used to derive a novel objective function. Finally, the obtained optimal cluster heads are utilized for the further Green IoT communication.

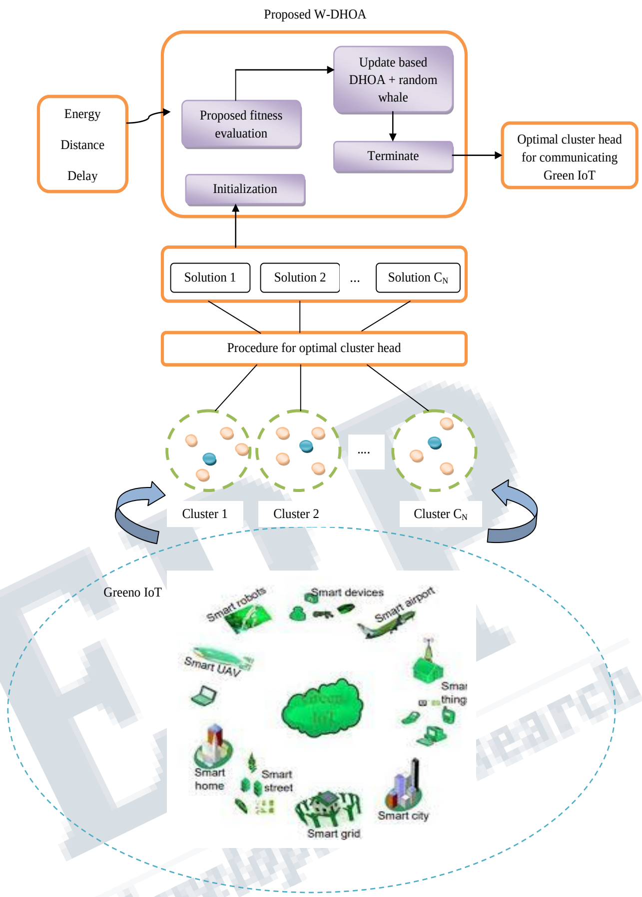

Fig. 2. Architecture of proposed clustering approach for energy efficient Green IoT

As per the proposed LEACH-based clustering in Green IoT, the developed objective function is represented in Eq. (2), which depends on Eq. (1).

$$Fit_0 = Delay \times a_r + Distance(1 - a_r) \quad (1)$$

$$Fit_* = Energy \times b_r + Fit_0(1 - b_r) \quad (2)$$

The terms $Delay$, $Distance$, and $Energy$ are the delay, distance and energy models in Green IoT. Moreover, a_r and b_r are the constants, where $a_r = 0.2$ and $b_r = 0.8$.

C. Energy Model

LEACH protocol works in multiple rounds that includes two steps such as setup stage and steady state step and it is depicted in Fig. 2. In the first set-up step, the clusters are produced and the selection of cluster head is performed. Every node of a specific group can contribute in the selection process of cluster head by producing a random priority value among 0 and 1.

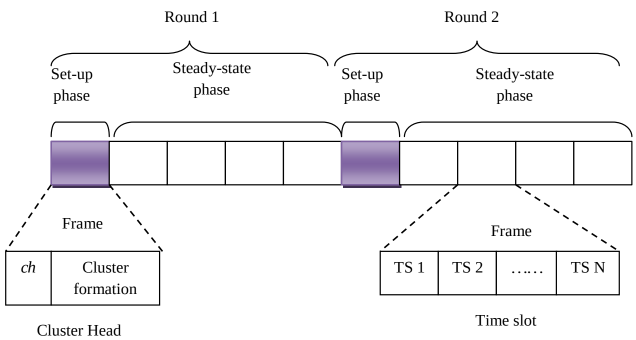

Fig.3 Different phases included in LEACH

The node is considered as the cluster head when the number for a member node is less than the threshold value $Th(n)$ based on Eq. (3). Moreover, the cluster head is also responsible for allotting TDMA programme for the respective cluster members.

$$Th(n) = \begin{cases} \dfrac{1}{1-k\left(rd \bmod \dfrac{1}{k}\right)} & \forall_n \in SN \\ 0 & Otherwise \end{cases} \quad (3)$$

In Eq. (3), the required percentage of nodes that has the ability to become cluster head is denoted as k, and the current round is indicated by rd. The set of nodes that have not contributed in the selection procedure of clustering in the earlier $\frac{1}{k}$ rounds is denoted as SN. The node that is selected as cluster head in a specific round rd is not permitted for contributing in the successive $\frac{1}{k}$ rounds. Thus, each sensor node in a group gets fair and equal chance for becoming the cluster head. Therefore, the energy dissipation in between the sensor nodes is dispersed equally in the network.

In steady state phase, the cluster member nodes transformed the sensed information to the corresponding cluster head node on the basis of the schedule of TDMA. In such a manner, the collision of intra-cluster is evaded. The key concept of LEACH protocol is to enhance the energy efficiency by selecting rotation-based cluster head selection process with a random number. Here, the first-order radio energy model is employed to communicate in the improved protocol. The first-order radio model is split into multi-path fading method and free space method on the basis of the distance among the sensing and the receiving nodes. Moreover, the communication channel is considered to be symmetric and the energy utilized by the sensor node in transmitting l bits or packets to a node mt meters away is denoted in Eq. (4) and Eq. (5). In addition, the energy used by a sensor node in receiving l packets is expressed in Eq. (6).

$$EN_{Thx}(l,mt) = EN_{Thx\_eke}(l) + EN_{Thx\_amp}(l,mt) \quad (4)$$

$$EN_{Thx}(l,mt) = \begin{cases} EN_{ele} * l + EN_{frs} * l * mt^2 & mt \le mt_0 \\ EN_{ele} * l + EN_{amp} * l * mt^4 & mt > mt_0 \end{cases} \quad (5)$$

$$EN_{RCx}(l) = EN_{RCx\_ele}(l) + lEN_{ele} \quad (6)$$

In the above equations, the energy used for each packet by the sender or receiver is denoted as EN_{ele}. The amplifier parameters of the transmission with respect to the free-space and the multi-path fading methods are denoted as EN_{frs} and EN_{amp}, respectively. Along with overhead, each packet is consisting of data packets. Moreover, the data bits hold the helpful data and the overhead has the detailed information associated with the packets namely encryption method employed for security and for addressing the source and destination, as well as coding model for transmitting the reliable data. The overhead size is constant without considering the size of the packet. The energy and spectrum consumed by the overhead might be neglected for the large packets and ease the WSN energy and spectral efficiency. Along with that, the improvement of throughput is also performed.

The number of data bits in each packet is denoted as N_{data} and the number of overhead bits is indicated by N_{ovh} using the energy allied with each data bits and overhead bits is represented as EN_{data} and EN_{ovh}, respectively. Therefore, the whole energy of the packets is given in Eq. (7).

$$EN_{pkt} = N_{data} \times EN_{data} + N_{ovh} \times EN_{ovh} \quad (7)$$

Assume, A, B, C, D, E, and F as the five cluster heads from five discrete clusters present in the network by having the initial energy as EN_{ini}. Once the first round is completed, all nodes will disperse the energy based on the different principles like packet size of the data, distance, and signal strength. Consider E and F as the two cluster

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heads that is not extended its energy and have enough power to be chosen as cluster head to the successive round. All the cluster heads are not appropriate for selecting the cluster head in the successive round as per traditional LEACH protocol. In this, the value of threshold limit PW_{thr} is set and any node that has an energy level exceeding it can continue to be cluster head by the similar cluster to the subsequent round. Thus, the energy consumed in the cluster head and the cluster formation reduces to an extensive amount.

In the network, n nodes are taken into consideration with CL percentage of clusters and the number of cluster head replacement is done by RP. The transferred packet sizes are denoted as PW_{lThx} and the received packet sizes are indicated by PW_{lRCx}. Assume $N = nCL$, which represents the count of clusters in each cluster. In cluster formation step, some amount of energy will be used in the replacement of cluster head procedure and this energy is represented as PW_{HR}, which is denoted in Eq. (8).

$$PW_{HR} = \{PW_{lThx} \cdot PW_{Thx} + PW_{lRPx} \cdot PW_{RPx}(nCL - 1)\}RP \cdot N \quad (8)$$

Therefore, the whole energy of each cluster PW_{WEC} is the product of initial power provided to each node and the entire nodes in a cluster is given by Eq. (9). Here, the initial energy EN_{ini} is given to each node. In order to measure the entire energy permitted in each cluster unit, the energy used by each cluster should be known for each i round, which is assessed by computing the energy cost if it represents as the cluster head and the member node. Hence, the mathematical equation is denoted in Eq. (10). Moreover, Eq. (10) can be written as shown in Eq. (11).

$$PW_{WEC} = EN_{ini} \times nCL \quad (9)$$

$$PW_{HR}(i) = \{(N_i - 1)PW_{lThx}PW_{Thx} * PW_{lRPx}PW_{RPx}\} + \{(N_i - 1)PW_{lThx}PW_{Thx} + (N_i - 1)PW_{lRPx}PW_{RPx}\} \quad (10)$$

$$PW_{HR}(i) = n(5N_i - 3)PW_{Thx} \quad (11)$$

The total amount of energy used for transferring the information from member node to cluster head is given by nPW_{Thx}. Later, the member node switches off the radio and goes to rest mode until the subsequent round of TDMA slot is obtained. Moreover, the cluster head eliminates the redundant information by aggregating the data in this stage. The energy used in this procedure is denoted as $n(N-1)PW_{RPx}$. The cluster head then transfers the combined information to the base node by disbursing $n(N-1)PW_{Thx}$ energy. In order to compute the value of threshold to the decision of cluster head substitution, the data regarding the number of rounds need to be obtained for active as member node in a cluster. The count of rounds of operation in the network is denoted as CNT_{Rnd} and it can be computed by Eq. (12).

$$CNT_{Rnd} = \frac{PW_{HR}}{PW_{WEC}} \times 100 \quad (12)$$

From Eq. (11) and Eq. (12), the minimum level of energy can be analyzed that is considered as optimum for the replacement process of cluster head based on Eq. (13).

$$Eenergy = PW_{Th} = CNT_{Rnd}(PW_{lThx} + PW_{lRPx})PW_{Thx} \quad (13)$$

Eq. (13) denotes the threshold value of power that is subjected to each LEACH protocol for increasing the lifetime of the network consequently minimizing the total energy of the network.

D. Distance Model

The numerical equation for measuring the distance is denoted in Eq. (14). The distance among the normal node and the cluster head is indicated by $G^{dist}(p)$. The numerical equation for $G^{dist}(p)$ is denoted in Eq. (15), normal nodes is denoted as $G^{dist}(q)$ and it is represented in Eq. which calculates the distance among the base station and the cluster head of each cluster in the network. In this, the distance between two (16). The value of $G^{dist}(p)$ must lie in between 0 and 1, and R is denoted as base station.

$$Dis\tan ce = \frac{G^{dist}(p)}{G^{dist}(q)} \quad (14)$$

$$G^{dist}(p) = \sum_{i=1}^{Q}\sum_{j=1}^{P}\|S_i - ch_j\| + \|ch_j - R\| \quad (15)$$

$$G^{dist}(q) = \sum_{i=1}^{Q}\sum_{j=1}^{P}\|S_i - S_j\| \quad (16)$$

E. Delay Model

The delay taken by the nodes in the Green IoT while transferring the data is represented in Eq. (17). Actually, the computational pattern of delay is expressed in Eq. (17)

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that must lie in between 0 and 1. The reduction of number of nodes in each group has the ability to reduce the delay.

$$Delay = \frac{\underset{j=1}{\overset{P}{Max}}(ch_j)}{Q} \tag{17}$$

In the above equation, the cluster head in the network is denoting in the numerator value and the whole count of nodes Q is represented in the denominator value.

IV. HYBRIDIZATION OF DEER HUNTING AND WHALE OPTIMIZATION ALGORITHM FOR ENERGY EFFICIENCT GREEN IOT

A. Solution Encoding

The diagrammatic representation of the solutions used for optimal cluster head selection in Green IoT is shown in Fig. 4. Here, the nodes from each cluster are taken as solution, which is further operated by the proposed W-DHOA for selecting the optimal cluster head.

Fig.4 Solution encoding for optimal clsuter head selection in Green IoT

As mentioned earlier, the proposed W-DHOA selects the best cluster head by concerning the objective constraints like energy, distance and delay.

B. Conventional Whale Optimization Algorithm

The conventional WOA [26] is motivated on the basis of the hunting mechanism of humpback whales, which are the huge whales of the baleen whales family. The interesting element of these whales is that it is having a specific mechanism, which is used to recognize they prey and encircle the prey. Eq. (18) and Eq. (19) denotes the encircling behaviour of whales.

$$A = \left| B.Pv^*(ti) - Pv(ti) \right| \tag{18}$$

$$Pv(ti+1) = Pv^*(ti) - C.A \tag{19}$$

In the above equations, the coefficient vectors are denoted as B and C. Moreover, the position vector of the acquired best solution is denoted as Pv^* and the position vector is given by Pv. The iteration is denoted as ti, and the absolute value is given by $|\ |$. Moreover, the element-by-element multiplication is given by '$\cdot$'. The coefficient vectors are represented in Eq. (20) and Eq. (21). Here, the term a is reduced accurately from 2 to 0 during the whole iterations and the random vector is denoted as rnd.

$$B = 2.rdn \tag{20}$$

$$C = 2a.rdn - a \tag{21}$$

In order to represent the bubble net methodology of humpback, there are two types of methods such as shrinking encircling mechanism and spiral update position mechanism taken into consideration. The shrinking method diminishes the value of a, which is there in Eq. (21). The spiral update process initially evaluates the distance among position of the prey (X^*, Y^*) and position of the whale (X, Y). Later, the spiral equation is provided between the position of the prey and the whale for mimicking the helix-shaped group of humpback whales as denoted in Eq. (22).

$$Pv(ti+1) = A'.e^{bc}.\cos(2\pi c) + Pv^*(ti) \tag{22}$$

In Eq. (22), the term $A = \left| B.Pv^*(ti) - Pv(ti) \right|$ indicates the distance among the prey and the whale, and the constant term is given by b, and a random number ranging in between -1 and 1 is given by c. To update the solution on the basis of shrinking encircling behaviour and the spiral method and the mathematical formula is given in Eq. (23), in which the random number lies in between 0 and 1 is given by d.

$$Pv(ti+1) = \begin{cases} Pv^*(ti) - C.A & if\ d < 0.5 \\ A'.e^{bc}.\cos(2\pi c) + Pv^*(ti) & if\ d \geq 0.5 \end{cases} \tag{23}$$

The term D is taken into consideration for searching the prey. The position vector Pv has random values lies in between in -1 and 1 for compelling search agent for going away from the reference whale. The mathematical equation is denoted in Eq. (24) and Eq. (25).

$$A = \left| B.Pv_{rdn} - Pv \right| \tag{24}$$

$$Pv(ti+1) = Pv_{rdn} - C.A \tag{25}$$

In the above equation, the random position vector is

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denoted as Pv_{rdn} .

C. Conventional Deer Hunting Optimization Algorithm

The inspiration of DHOA [27] is inspired by the hunting behaviour of human for chasing towards the deer. The main intention of DHOA is to obtain the optimal position for shooting the deer. Moreover, it has few requirements that are quite complex for the human in order to hunt the deer. The visual power of deer is five times more than humans. At first, the population of the hunter is given in Eq. (26), in which the whole number of hunter's population is given by N .The position and wide angle of the deer are initialized as hunter's best positions. Consider the circle as search space, and the wind angle follows the circumference of the circle and it is given in Eq. (27) and the position angle is denoted in Eq. (28).

$$Pv = \{Pv_1, Pv_2, \cdots, Pv_N\} \quad 1 < pop < N \tag{26}$$

$$\theta_{ti=} 2\Pi rd \tag{27}$$

$$\phi_{ti} = \theta + \Pi \tag{28}$$

In the above equations, the term rd indicates the random number. The position of the leader and the successor are considered and they are denoted as Pv^{lr} and Pv^{sr} , respectively. The position of the leader is taken as the best position of the hunter. Further, each hunter strives to be in the best location, for that the update process starts here. Consequently, the encircling behaviour is denoted in Eq. (29).

$$Pv_{ti+1} = Pv^{lr} - E \cdot e \cdot \left| F \times Pv^{lr} - Pv^{ti} \right| \tag{29}$$

In the above equation, the coefficient vectors are denoted in Eq. (30) and Eq. (31), respectively. The term g denotes the parameter that lies in between -1 and 1, and the random number is denoted as h , which lies in between 0 and 1. The position angle is considered in the update rule and the search space improvement is performed. The visualization angle of the prey is denoted in Eq. (32). The position angle's update process is represented in Eq. (33) and that is measured based on the wind angle. In order to update the position angle for the successive iteration, the numerical equation is denoted in Eq. (34).

$$E = \frac{1}{4}\log\left(ti + \frac{1}{ti_{\max}} \right) g \tag{30}$$

$$F = 2 \cdot h \tag{31}$$

$$vsa_{ti} = \frac{\Pi}{8} \times rad \tag{32}$$

$$df_{ti} = \theta_{ti} - dva_{ti} \tag{33}$$

$$\phi_{ti+1} = \phi_{ti} + df_{ti} \tag{34}$$

In addition, the position update is performed by considering the position angle as shown in Eq. (35). The encircling behaviour in exploration phase is assumed by changing the vector F . Thus, the position update is performed based on the successor's position instead of the first best solution. The global search equation is denoted in Eq. (36).

$$Pv_{ti+1} = Pv^{lr} - e \cdot \left| \cos(t) \times Pv^{lr} - Pv_{ti} \right| \tag{35}$$

$$Pv_{ti+1} = Pv^{sr} - E \cdot e \cdot \left| F \times Pv^{sr} - Pv_{ti} \right| \tag{36}$$

The update process of position is performed in each iteration up to the best solution is obtained.

D. Proposed W-DHOA

The conventional DHOA is motivated by the hunting behaviour of humans in order to hunt the deer. The traditional DHOA is having many advantages such as the high sensitivity when compared over other heuristic algorithms, fast convergence rate, and acts as the best model in solving all the optimization problems. However, there are few conflicts with the existing DHOA algorithm such as poor constraint handling capacities, and less capability for solving different optimization problems. Moreover, the conventional WOA have more benefits such as high performance in solving optimization problems, high reliability, and less power loss. As WOA is having high capability in solving distinct optimization problems and has high performance, the proposed model is planning to integrate the WOA with DHOA and generate a hybrid model named W-DHOA. Here, if $(e < 1)$, then the leader's and successor's positions of DHOA are updated. Otherwise, the random position of the whale optimization is updated by Eq. (7). In earlier works, more optimization models were merged for introducing a new hybrid optimization method. These hybrid models are reported for providing the best results for specific search problems. Moreover, these methods hold the advantages of discrete optimization algorithms in order to acquire fast convergence. The convergence behaviour of hybrid algorithm is found to be best when compared over other models [29].

Algorithm 1: Pseudo code of proposed W-DHOA

```
Hunter's population is initialized as Pv
While (ti < ti_max)
    for each solution in the population
        Fitness function of each solution is calculated
        Update vsa, df, e, E, F, and g
        if (e < 1)
            if (|F| >= 1)
                Update individual's position by Eq. (29)
            else
                Update individual's position by Eq. (36)
            end if
        else
            Update individual's position by Eq. (35)
        else
            Update the random position of WOA by Eq. (24)
        End if
    end for
    Calculate fitness for each solution
    Update Pv^lr and Pv^sr
    ti = ti + 1
    return Pv^lr
```

V. RESULTS AND DISCUSSIONS

A. Experimental Setup

The developed LEACH-based energy efficient protocol for M2M communications in Green IoT was simulated in MATLAB 2018a, and the analysis was carried out. The simulation was performed for analyzing the performance of the proposed W-DHOA over other meta-heuristic algorithms. The area of the network considered for the experiment was $100m \times 100m$ with base station at centre. The number of nodes was fixed as 100, and it was varied for the experimental analysis. The initial energy of the network was assigned as 5pJ/bit/m^2, energy of the power amplifier was taken as 0.0013pJ/bit/m^2, energy of the free space model was taken as 10pJ/bit/m^2, transmitter energy was taken as 50pJ/bit/m^2, and data aggregation energy was taken as 5pJ/bit/m^2. The population size was assumed as 10 and the number of iterations performed was 10. The performance analysis of the proposed W-DHOA was compared over FF [30], GWO [31], WOA [26], and DHOA [27] with respect to "cost function, number of alive nodes, log(number of alive nodes), normalized energy, and normalized network energy" for both 50 IoT devices, 100 IoT devices, and 200 IoT devices as well in different area.

B. Analysis of using 50 IoT devices in 100×100 m

The analysis of the develped and suggested models for 50 IoT devices is shown in Fig. 5. In Fig. 5 (a), the convergence analysis of the proposed and the conventional models is depicted. At 1st iteration, the proposed model is having high cost function but as the process is continuing the proposed model is exhibiting less cost function. At 10th iteration, FF model is having maximum cost function, whereas the proposed W-DHOA is having minimum cost function. Moreover, GWO is having less cost function, after that DHOA is exhibiting less cost function. Next, WOA is having maximum cost function. From the 1st iteration till the last iteration, the FF and WOA algorithm is maintaining the same cost function. On the degree of improvement, at 10th iteration, the proposed W-DHOA is 0.8% better than GWO, 2.1% better than DHOA, and 2.5% better than WOA. In Fig. 5 (b), the analysis of the suggested and traditional models in terms of number of alive nodes is described. Until 500 rounds, the proposed and the traditional methods are alive with 50 IoT devices. After 500th round, the number of alive nodes is reducing as the number of rounds is increasing. The distance between the devices in specific rounds for the number of alive nodes with respect to distance in IoT devices is shown in Fig. 5 (c). The suggested W-DHOA is having the maximum number of alive nodes as the distance increases. The analysis of the developed and the classical models with respect to normalized energy is shown in Fig. 5 (d). At 2000th round, the normalized energy of the proposed and the DHOA is maximum. Moreover, FF is having minimum energy, whereas WOA is having minimum normalized energy. Fig. 5 (e) shows the performance of the developed W-DHOA and the conventional models concerning normalized network energy with respect to energy difference. Here, the proposed W-DHOA is exhibiting maximum energy when compared over other models. In Table II, the overall transmission delay of the developed W-DHOA and the meta-heuristic algorithms is shown with respect to count of rounds is shown. The delay of the proposed W-DHOA is 16.7% better than FF, 10.1% better than GWO, 1.3% better than WOA, and 9% better than DHOA at 1st round. When considering the 2001st round, the transmission of the presented W-DHOA is 2.7% advanced than FF, 9% advanced than GWO, 6.2% advanced than WOA, and 8.7% advanced than DHOA.

Hence, the proposed W-DHOA is well suitable for improving the lifetime of the network.

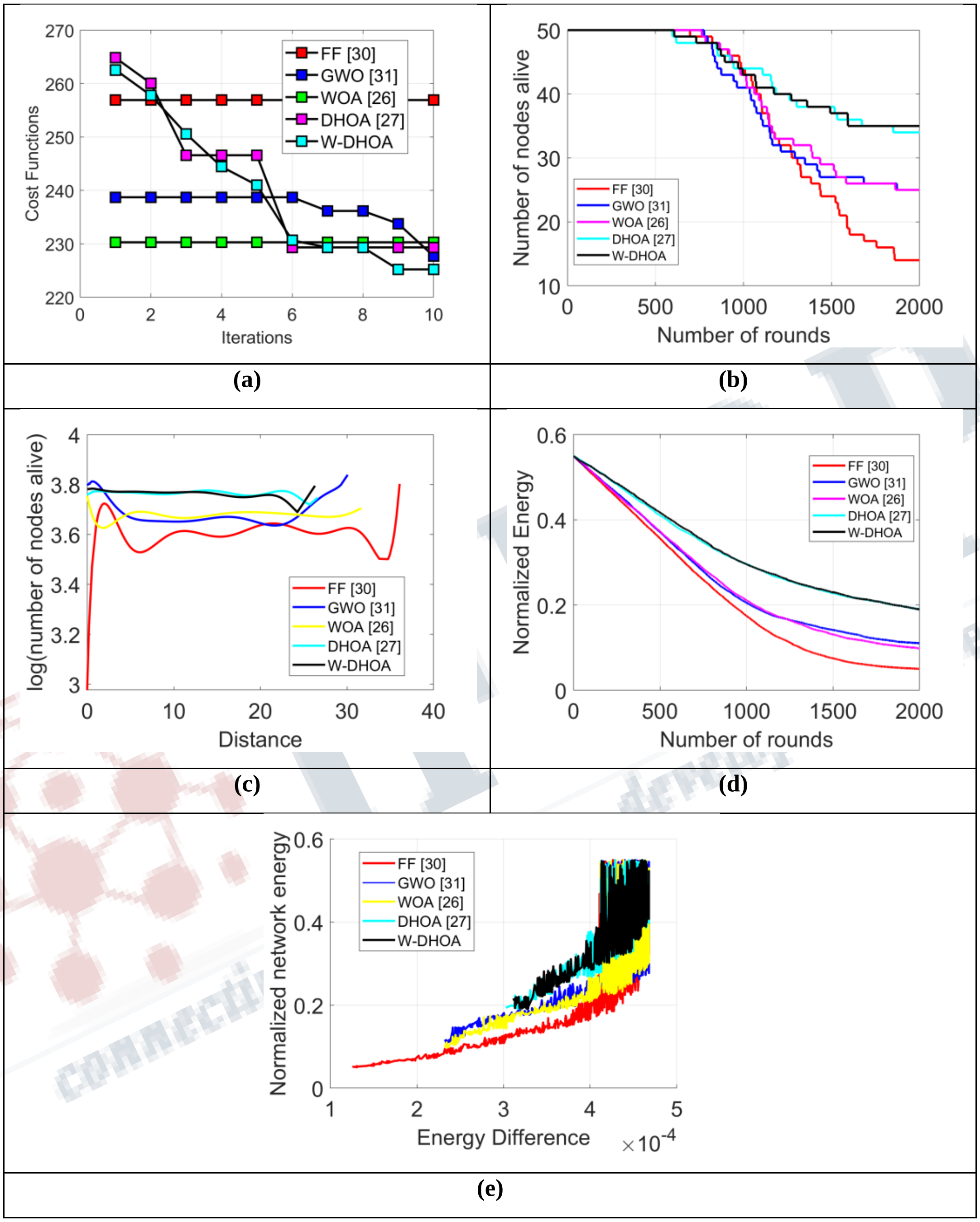


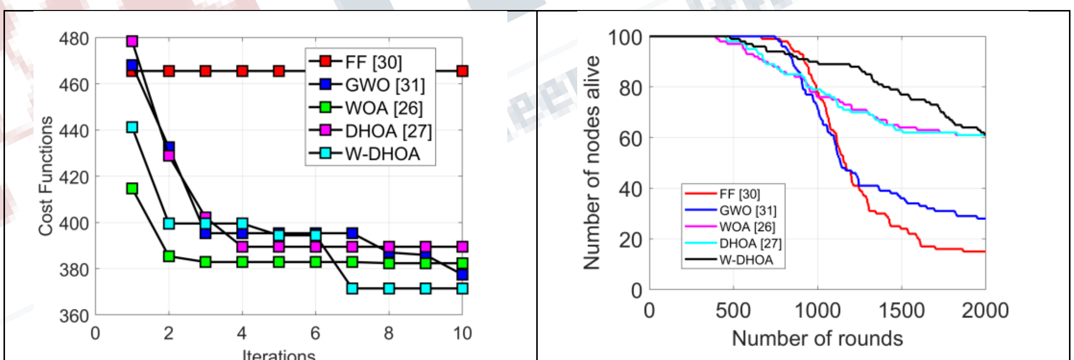
Fig.5 Performance analysis of proposed and conventional cluster head selection for energy efficienct Green IoT using 50 IoT devices (a) Convergence analysis, (b) Number of alive nodes, (c) Number of alive nodes with distance, (d) Normalized energy, and (e) Normalized network energy

Table.2 Performance analysis interms of delay for the proposed and conventional algorithms using 50 IoT devices in 100×100m

Rounds	FF [30]	GWO [31]	WOA [26]	DHOA [27]	W-DHOA
1	1.4838	1.3758	1.2532	1.3587	1.2357
100	1.456	1.4008	1.4434	1.2636	1.3417
225	1.4325	1.3587	1.3963	1.3587	1.3025
500	1.3928	1.4928	1.3587	1.3587	1.233
725	1.4606	1.2964	1.3587	1.4008	1.3731
1000	1.3655	1.3963	1.3587	1.3587	1.3963
1225	1.1784	1.3587	1.2784	1.3012	1.4417
1500	1.3176	1.2964	1.3963	1.4008	1.473
1726	1.3827	1.2964	1.3431	1.3587	1.278
2001	1.3099	1.4008	1.3587	1.3963	1.2735

C. Analysis of using 100 IoT devices in 100×100 m

For 100 IoT devices, the performance analysis of the proposed and the conventional models is shown in Fig. 6. In Fig. 6 (a), the convergence analysis of the proposed W-DHOA is shown. At last iteration, the recommended W-DHOA is having minimum cost function. At 7th iteration, the suggested W-DHOA is exhibiting minimum cost function, followed by WOA. Later, DHOA is having minimum cost function and GWO is having minimum cost function. Finally, FF is having maximum cost function. FF algorithm is exhibiting the similar cost function from the 1st iteration to the last iteration, which is maximum. The proposed and the traditional methods are alive at 100 until 500 rounds. From there, the alive nodes start decreasing as the number of rounds is increasing based on Fig. 6 (b). In Fig. 6 (c), the proposed W-DHOA is having maximum number of alive nodes as the distance is increasing. From Fig. 6 (d), the normalized energy of the developed W-DHOA is maximum at 1st round and it started decreasing until 2000th round. The performance of the presented W-DHOA and the heuristic algorithms is shown in Fig. 6 (e) with respect to normalized network energy. The proposed model is having maximum network energy as the energy difference is increasing and FF is having minimum energy at first based on Fig. 6 (e). The overall transmission delay of the proposed and the conventional models with respect to number of rounds using 100 IoT devices is shown in Table III. From Table III, the delay of the proposed W-DHOA is 2.9% superior to FF, 10.9% superior to GWO, 0.9% superior to WOA, and 3.2% superior to DHOA when considering the number of rounds as 100. At 1500 rounds, the transmission delay of the recommended W-DHOA is 185% enhanced than FF, 15.9% enhanced than GWO, 16.2% enhanced than WOA, and 8.3% enhanced than DHOA. Thus, it is concluded that the proposed model is outperforming the conventional models in LEACH-based protocol in M2M communication.



(a) (b)

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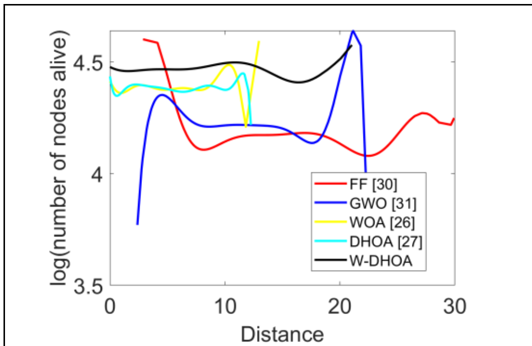

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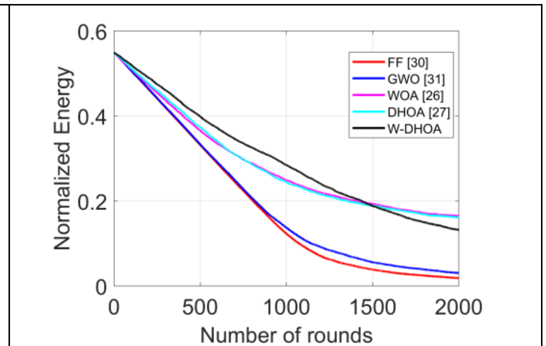

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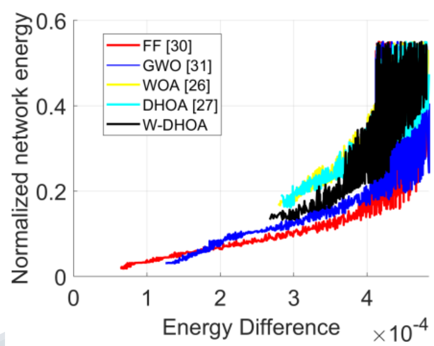

(e)

Fig.6 Performance analysis of proposed and conventional cluster head selection for energy efficient Green IoT using 100 IoT devices (a) Convergence analysis, (b) Number of alive nodes, (c) Number of alive nodes with distance, (d) Normalized energy, and (e) Normalized network energy

Table.3 PERFORMANCE ANALYSIS INTERMS OF DELAY FOR THE PROPOSED AND CONVENTIONAL ALGORITHMS USING 100 IOT DEVICES in 100×100m

Rounds	FF [30]	GWO [31]	WOA [26]	DHOA [27]	W-DHOA
1	1.9068	1.2233	1.2558	1.2516	1.0523
100	1.3065	1.2821	1.2558	1.2284	1.2681
225	1.433	1.2233	1.234	1.2519	1.4303
500	1.4491	1.3671	1.234	1.2558	1.5096
725	1.3231	1.2558	1.2516	1.212	1.4339
1000	1.2461	1.2558	1.2286	1.372	1.4943
1225	1.1994	1.2558	1.139	1.2516	1.1504
1500	1.4042	1.3703	1.3738	1.2558	1.1511
1726	1.4589	1.2558	1.2472	1.3364	1.1897
2001	1.3157	1.2558	1.2558	1.2821	1.135

D. Analysis using 200 IoT devices in 150×150 m

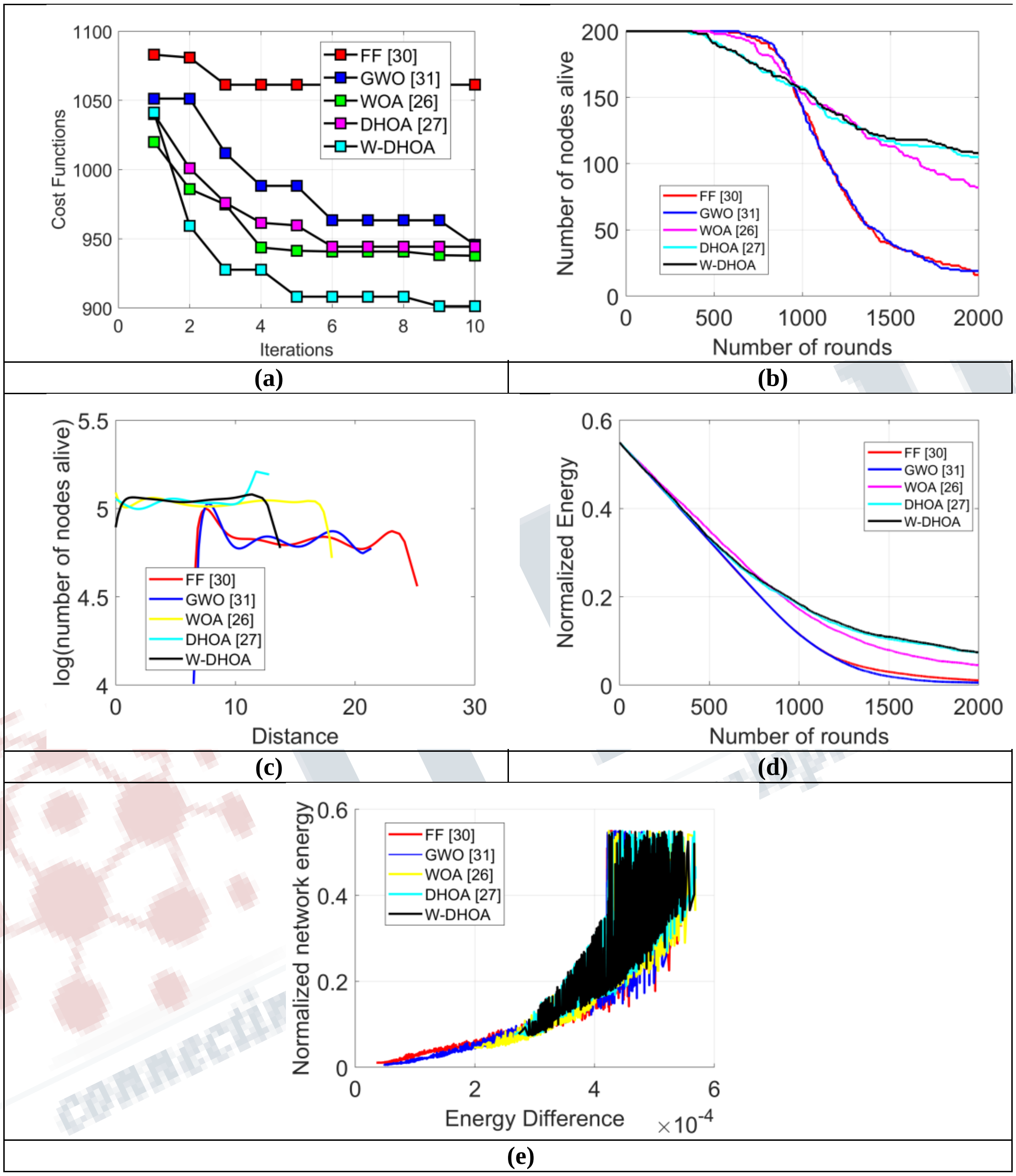

Fig.7 Performance analysis of proposed and conventional cluster head selection for energy efficienct Green IoT using 200 IoT devices in 150×150m (a) Convergence analysis, (b) Number of alive nodes, (c) Number of alive nodes with distance, (d) Normalized energy, and (e) Normalized network energy

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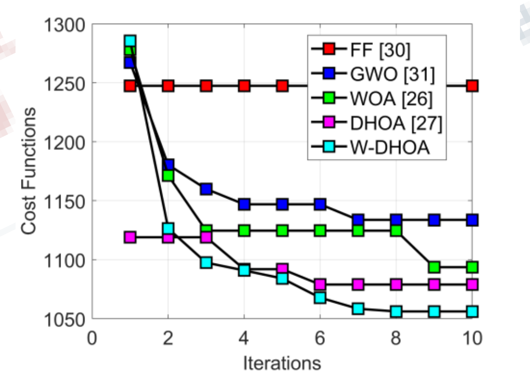
Table 4 PERFORMANCE ANALYSIS INTERMS OF DELAY FOR THE PROPOSED AND CONVENTIONAL ALGORITHMS USING 200 IOT DEVICES IN 150×150m

Rounds	FF [30]	GWO [31]	WOA [26]	DHOA [27]	W-DHOA
1	2.983	3.197	2.4793	2.1163	2.1163
100	3.3559	2.6213	2.2155	2.3454	2.3217
225	2.9477	2.8998	2.0652	2.4207	2.1125
500	2.8764	2.6364	2.2365	2.1542	2.8073
725	2.993	2.8533	2.1999	2.2099	2.3797
1000	2.9994	2.8829	2.1801	2.3123	2.1163
1225	3.18	3.1087	2.1043	2.2315	2.1163
1500	3.132	2.7989	2.1399	2.302	2.3245
1726	2.806	2.6652	2.1244	2.224	2.1163
2001	3.4023	2.8062	2.0923	2.2315	2.1517

E. Analysis using 200 IoT devices in 200×200 m

For 200 IoT devices, the performance analysis of the improved W-DHOA and the traditional methods is portrayed in Fig. 8. Here, the convergence analysis, number of alive nodes, number of alive nodes with respect to distance, normalized energy, and normalized network energy is given. The cost function of the introduced W-DHOA is minimum at 10th iteration, which is shown in Fig. 8 (a). Later, DHOA is having the minimum cost function, followed by WOA, GWO, and FF, respectively. When considering the 1st iteration, the proposed model is having maximum cost function, followed by WOA, GWO, FF, and DHOA, respectively. From Fig. 8 (b), the number of alive nodes of the suggested W-DHOA and the traditional algorithms per number of rounds is shown. In this figure, the number of alive nodes of all the algorithms is maximum and same until 500 rounds. Thereafter, slowly decreasing the number of alive nodes as the number of rounds keeps on increasing. From the analysis, it is confirmed that the proposed W-DHOA is having more number of alive nodes when compared over all the other algorithms. The performance of the suggested W-DHOA and the conventional models with respect to distance is shown in Fig. 8 (c). From Fig. 8 (c), when considering the distance as 16, the number of alive nodes of the proposed W-DHOA is maximum when compared over other machine learning algorithms. Fig. 8 (d) shows the normalized energy of the proposed W-DHOA and the classical algorithms. At 2000th round, the proposed model is exhibiting maximum energy. Fig. 8 (e) shows the normalized network energy of the suggested W-DHOA and the traditional algorithm. At 2, the network energy of the proposed model is maximum and it continues until last. The overall transmission delay of the developed W-DHOA and the conventional models is shown in Table V. From Table V, the delay of the proposed W-DHOA is 18.9% superior to FF, 8.6% superior to GWO, and 1.2% superior to DHOA. At last, it is confirmed that the developed W-DHOA is performing well when compared over other algorithms.



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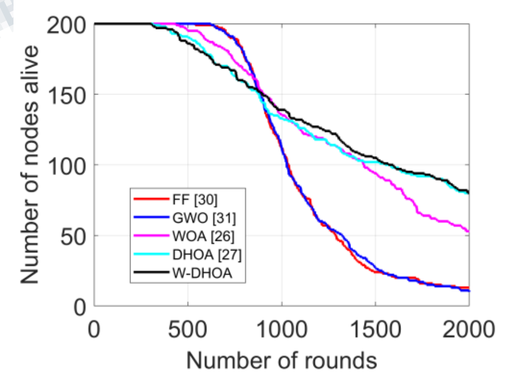

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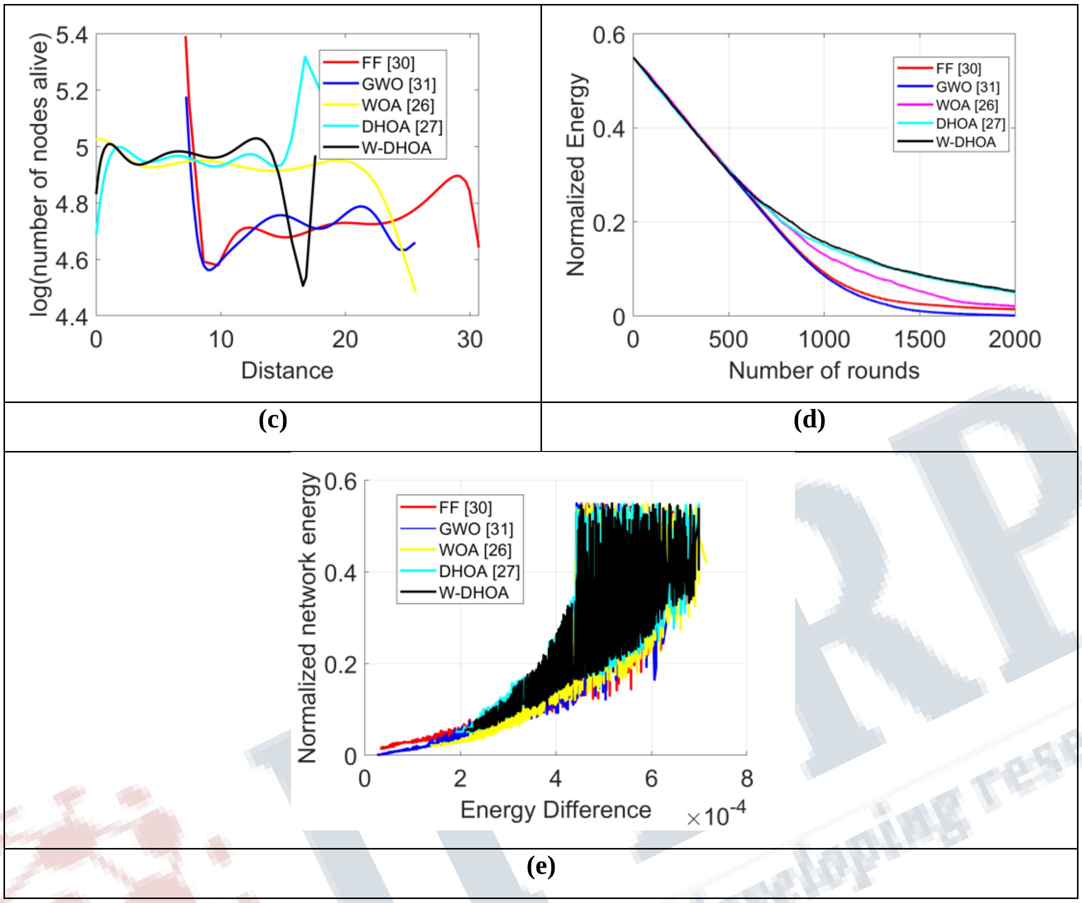

Fig.8 Performance analysis of proposed and conventional cluster head selection for energy efficienct Green IoT using 200 IoT devices in 200×200m (a) Convergence analysis, (b) Number of alive nodes, (c) Number of alive nodes with distance, (d) Normalized energy, and (e) Normalized network energy

Table.5 PERFORMANCE ANALYSIS INTERMS OF DELAY FOR THE PROPOSED AND CONVENTIONAL ALGORITHMS USING 200 IOT DEVICES in 200×200m

Rounds	FF [30]	GWO [31]	WOA [26]	DHOA [27]	W-DHOA
1	3.6245	3.2166	2.9382	2.9764	2.9382
100	4.4089	3.3359	2.9533	2.9382	2.9382
225	3.7448	3.0037	2.9382	2.9382	2.9513
500	3.929	3.4158	2.964	2.9788	2.9382
725	4.1759	3.6123	2.9306	2.9489	2.9382
1000	4.3425	3.9617	3.1635	2.9419	3.5003
1225	4.3869	3.4642	2.9382	2.9974	2.9889
1500	4.2076	3.667	2.9587	3.0156	2.9171
1726	3.4945	3.6758	3.0938	3.0852	3.0153
2001	4.1793	3.7465	2.9997	2.9176	2.8596

VI. CONCLUSION

This paper has presented a new methodology named energy efficient protocol for M2M communication in Green IoT by a clustering mechanism integrated with hybrid meta-heuristic model. The energy efficient Green IoT was introduced using the proposed LEACH protocol that decreased the power usage at distinct levels. The aim of the suggested protocol was to reduce the usage of energy of M2M communication, by reducing the distance among the devices, and delay while transferring the information by introducing the cluster head selection. The developed LEACH protocol employed the hybrid meta-heuristic algorithm named W-DHOA for obtaining the objective. The combination of these two meta-heuristic methods in LEACH protocol performed best in selecting the cluster head for minimizing the energy utilization, therefore increasing the lifetime of the network. From the analysis, at 10th iteration, the cost function of the proposed

W-DHOA was 0.8% better than GWO, 2.1% better than DHOA, and 2.5% better than WOA. Finally, it is concluded that the proposed W-DHOA method is well suitable for energy efficient Green IoT.

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