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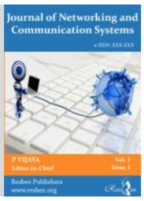

Cluster Head Selection in IoT Using Enhanced Self Adaptive Bat Algorithm

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Abstract: With sufficient technological advancements and prosperous demand for digital aids in work environments and daily life which goes with it, technologies are needed to derive this application domain to the following level. Internet of Things (IoT) is considered as a real visualization for such technologies. The main aim of this paper is to present an Enhanced Self-Adaptive Bat algorithm (ESABA) in order to attain the energy-aware clustering protocols and Cluster Head Selection (CHS) under Wireless Sensor Networks (WSN) based on the IoT. In WSN, besides with the parameters such as delay, distance, energy of sensor nodes, this experimentation considers both the temperature and load of IoT devices. It performs an important performance analysis regarding normalized energy, network efficiency, and temperature and loads for the selection of cluster head after modeling the experimentation. The performance analysis compares with the efficiency of proposed ESABA against conventional Artificial Bee Colony (ABC), Whale Optimization Algorithm (WOA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO). Finally, the result from the experimentation model shows the successful performance of proposed ESABA in CHS therefore the lifetime of the network is prolonged.

Keywords*:* WSN; IoT; Energy-Aware; Load; Temperature

Nomenclature

Abbreviations	Descriptions
IoT	Internet of Things
ABC	Artificial Bee Colony
WSN	Wireless Sensor Network
ICT	Information and Communication Technology
EH	Energy Harvesting
WOA	Whale Optimization Algorithm
EHWSNs	Energy Harvesting WSN
PSO	Particle Swarm Optimization
CHS	Cluster Head Selection
WAMS	Wide Area Measurement Systems
EE-CATS	Energy-Efficient Context-Aware Traffic Scheduling
GWO	Grey Wolf Optimization
BA	Bat Algorithm
EC	Energy Consumption
PER	Pulse Emission Rate
QoS	Quality-of-Service
PA	Power Amplifier
SNs	Sensor Nodes
BS	Base Station
AMI	Advanced Meter Infrastructure

1. Introduction

Generally, IoT is considered as the latest ICT model for the distributed embedded communication systems and computing. Moreover, the IoT is an intelligent network model in which a huge amount of distinctively individual objects or things for instances: actuators, wireless devices, and sensors are interrelated to carry out complex tasks in supportive ways [11].In recent times, IoT applications on the basis of the heterogeneous WSN model are attracting more interest from the research area [12], The WSN-based IoT model is to find out the applications in numerous domains, like Smart Transportation, Smart Home, Smart Grid, Smart Health-care, and Smart City by allowing simple access and interface with objects or things [13]. In the media, the IoT is not considered as just a buzzword; it is flattering realism. The surfacing of IoT tends us into the latest epoch of creativity and innovation. This sets maximum prospect on both the study industry and area for carrying the essential technological developments, which will permit for the appearance of novel IoT applications.

The installation of powering billions of embedded devices into the surroundings is considered as the main concerns in that IoT features. Battery-based solutions are subject to expensive as well as unfeasible, it is because of the need for replacement or recharging. For numerous IoT applications, EH emerges as a feasible choice, however, it has two limitations. Initially, it is frequently an unreliable energy source. Subsequently, there is still a big gap among the energy it can transport and the necessary energy resources for numerous IoT technologies. For mission significant IoT technologies, like health-care, implementing a task prior to termination of energy budget is essential.

Nowadays, EH shows a potential lifetime expansion choice for WSN. While comparing with the battery-only designs, EH nodes need minimum energy storage ability for unremitting, enduring operation. EH, still, can be subjected to immense unpredictability [1]. In many tremendous scenarios, this can mean no energy is produced for extensive periods of time. To deal with harvesting inconsistency, the service of the systems is usually minimized as the available energy reduces [2]. Particular technologies, nevertheless, for specific tasks need an always-on domain that is essentially unsuited with service deprivation. One instance is a sensing system which requires to incessantly recording the data although can suspend the transmission and processing of the recorded data for periods for maximum energy accessibility.

In the routing protocols models, the materialization of developed EH methods has endorsed a paradigm shift for EHWSNs, from energy-aware [7] [8] to energy-harvesting-aware [9]. The frequently exploited approach in the majority of these routing techniques is on the basis of the Dijkstra's shortest path" method to identify the low-cost route to forward data packets from a particular SN to the receiver that is the base station [10] [19]. In these approaches, the cost metrics considered as the hop count, the amalgamation of throughput, delay or the delay, as well as energy expenditure.

The major contribution of this paper is to present an Enhanced Self-Adaptive Bat Algorithm in order to attain the CHS in WSN-IoT network. It considered the sensor nodes parameters namely delay, energy, and IoT devices such as load and temperature. Finally, the proposed method is compared with various existing PSO, GWO, ABC, and WOA algorithms.

2. Literature Review

In 2018, Thien Duc Nguyen et al [1], developed a design of EH-aware routing protocol in the existence of relating to the energy sources for heterogeneous IoT networks. Moreover, they have presented a novel routing method EHARA that was improved by incorporating a novel parameter named energy back-off. Integrating with various EH methods, the presented method enhances the lifetime of the nodes and the QoS of the networks in energy availability and variable traffic load states. Moreover, it examines the performance of the system metrics for different EH states.

In 2019, Aamir Mahmood et al [2], studied a cross-layer optimization for minimum-power wireless related with reliability-aware technologies while taking into consideration of both the nonideal characteristics and the constraints of the hardware in IoT devices. Moreover, EC techniques were modeled, which apprehends the packet overhead, the energy cost of transceiver circuitry, PA, packet error statistics, and so forth in distributing a functional data bit. For a perfect and two practical nonlinear PA representations, the EC model was derived. To integrate packet error statistics, easy method was developed, by means of the elementary modes.

In 2017, Kyriakos Georgiou et al [3] worked on IoT, which embers an entire innovative globe of embedded technologies. The majority of these technologies were on the basis of the intensely embedded systems, which need to function on restricted or unreliable sources of energy, like batteries or EH. For such applications, meeting the energy needs was an inflexible concern that intimidates the prospect development of the IoT. Moreover, this article discussed the requirement for energy simplicity in software progress and put emphasis on how such simplicity can able to understood to aid undertaking the IoT energy challenge.

In 2018, Leila Ismail and Huned Materwala [4], worked on the implementation of cloud pervasive in the IoT mode, which creates the fundamental data centers intensify issues such as the operational costs and environmental carbon footprint that happen from the maximum energy utilization of computing servers. Evaluation and classification of thirteen different techniques utilizing a unified setup were stated in this paper, It was done with aspire of attaining an objective comparison.

In 2018, P. Anagnostou et al [5], presented a Torpor, which was a power-aware hardware scheduler that incessantly observes harvesting power and in amalgamation with its software runtime, dynamically stimulates system functions based on the obtainable energy and its rate of change. Using some fundamental purpose in hardware, Torpor acquires a minimum power overhead in incessant monitoring, when the software runtime offers a maximum flexibility degree to allow various scheduling policies.

In 2017, Bilal Afzal et al [6], worked on the competent allocation of resource to the Wi-Fi-on the basis of the IoT devices in multi-hop IoT infrastructures. At first, as indicated by their heterogeneous traffic demand and mapped into the different weighted superiority classes, the IoT applications were characterized. Subsequently, for IoT devices, the context-awareness was developed and an optimization technique inhibited by their context priorities and service quality requirements was modeled. Moreover, An EE-CATS technique was presented in which the convergence of framework was particular by a sub-gradient projection technique.

3. Cluster Head Selection in IoT

3.1 IoT Enables WSN

Generally, WSN is considered as a network, which consists of an innumerable number of SNs. In the network, those SNs are spatially positioned for examining a phenomenon of a few types, in compliance with the application in consideration. In reality, the accessible nodes primarily comprise of the transceiver, microcontroller, memory units and power units that soak up additional power that they become frayed out in a limited period. The lifetime of network minimizes with the maximum number of nodes. Conversely, high preservation of energy guides to maximize the lifetime that can be done possibly by the implementation of clustering method. Since it is entire nodes in a cluster excluding the CH are held back from utilizing their energy to increase singular communication with the BS. Fig 1 demonstrates the architecture diagram of the IoT enabled WSN for cluster head selection.

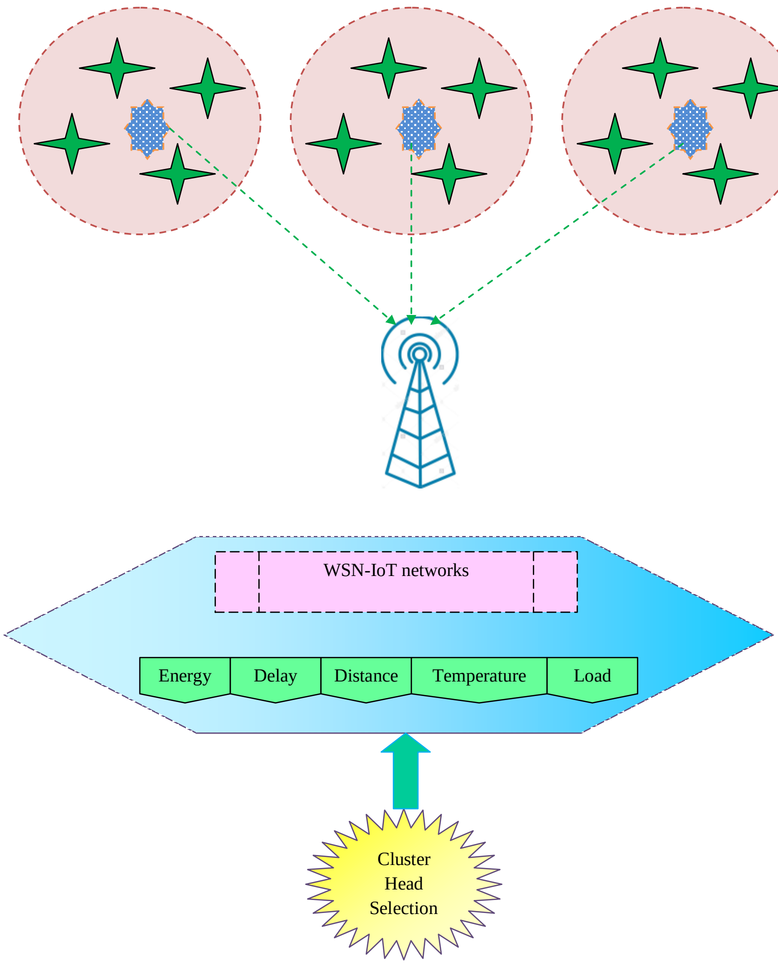

Fig. 1. *Architecture diagram of IoT enabled in WSN for Cluster Head Selection*

Let us consider N_{cl} number of clusters that are indicated as Cl_i in a WSN, whereas, $i = 1,2,...,N_{cl}$. In each cluster, the number of clusters might deviate and N_{ij} denotes the node in any of the cluster, whereas $i = 1,2,...,P$ and $j = 1,2,...,Q$. In each node, CH is chosen from the complete nodes that are indicated as CLH_i. Moreover, the parameters such as conserved energy, distance among the nodes, and packet transmission delay must be well-thought-out when choosing a node as the CH in WSN. Consequently, exclusive of the other SNs, merely the CHs in the network have through communiqué with the BS. In the scenario of IoT and WSN incorporation, it is even highly complex to choose the CH as it needs to challenge the network features of IoT beside with the WSN features. Hence, it is necessary to model an effectual technique relating to all the parameters, hence that the network lifetime can be improved.

3.2 Objective Function

The significant parameters like distance, delay, and energy, are utilized in WSN in order to perform efficient CHS. On the other hand, the parameters related with the IoT network must be represented in the scenario of IoT network that is temperature and load. Hence, the presented CHS in WSN-IoT method contemplates distance, energy, load, delay, and temperature. In fact, the effectual performance of the network can be attained if the conserved energy is maximum and distance, delay, load, as well as temperature are minimal. Eq. (1) to Eq. (3) indicates the proposed objective function, whereas δ and γ are the constants that encompass the values 0.9 and 0.3, correspondingly.

$$FT_1 = ff^{energy}\ {}^{1}\!/_{ff^{load}} + ff^{energy}\ {}^{1}\!/_{ff^{temperature}} \tag{1}$$

$$FT_2 = \delta\ {}^{1}\!/_{ff^{distance}} + (1-\delta)FT_1 \tag{2}$$

$$FT_3 = \gamma FT_2 + (1-\gamma)\ {}^{1}\!/_{ff^{delay}} \tag{3}$$

In this experimentation, the calculation of five parameters are determined and mathematically modeled as below:

Energy: In eq. (4), the energy consumption of WSN-IoT network is stated, and in eq. (6) $ER(N_i)$ represents the energy of i^{th} normal node and $ER(CLH_j)$ represents the energy of j^{th} CH, correspondingly.

$$ff^{energy} = \frac{ff^{energy}(q)}{ff^{energy}(p)} \tag{4}$$

$$ff^{energy}(q) = \sum_{j=1}^{Q} pER(j) \tag{5}$$

$$pER(j) = \sum_{\substack{i=1 \\ i\in j}}^{P} \left(1 - ER(N_i) * ER(CLH_j)\right);\ \ 1 \le j < Q \tag{6}$$

$$ff^{energy}(p) = Q * \operatorname*{Max}_{i=1}^{P}\left(ER(N_i)\right) * \operatorname*{Max}_{j=1}^{Q}\left(ER(CLH_j)\right) \tag{7}$$

Distance: In eq. (8), the mathematical procedure for distance calculation is stated, $ff^{energy}(q)$ denotes the distance among CH and normal node as well as among the BS and CH of the network as stated in Eq. (9) and $ff^{energy}(p)$ represents the distance among two normal nodes which is exhibited in eq. (10). The value of $ff^{distance}(q)$ must be in the range [0, 1].

$$ff^{distance}(q) = \frac{ff^{distance}(q)}{ff^{distance}(p)} \tag{8}$$

$$ff^{distance}(q) = \sum_{i=1}^{P}\sum_{j=1}^{Q} \left\|N_i - CLH_j\right\| + \left\|CLH_j - A\right\| \tag{9}$$

$$ff^{distance}(q) = \sum_{i=1}^{P}\sum_{j=1}^{Q} \left\|N_i - N_j\right\| \tag{10}$$

Delay: The eq. (11) states the nodes delay and the connected IoT devices in the transmission. In reality, the delay value stated in eq. (11) must be amid the range [0, 1]. The reduction of a number of nodes in each cluster can typically decrease the delay. As eq. (11), the numerator value represents CH in WSN, and denominator value represents the total number of nodes.

$$ff^{delay} = \frac{\underset{j=1}{\overset{Q}{Max}}\left(CLH_j\right)}{P} \tag{11}$$

Temperature and Load: The temperature and load of the IoT devices are estimated by utilizing the appropriate temperature and load devices by Xively (http://www.xively.com/xively-iotplatform).

4. Optimized Cluster Head Selection Approach on IoT

4.1 Conventional BA

The conventional BA was enthused by the echolocation behaviour, which is shown by bats while searching food [14]. Into their surroundings, bats produce ultrasonic pulses and pay attention to the echoes to help with navigation and hunting [15]. The optimization function of the conventional BA is on the basis of the loudness L, frequency ff, and PER (ER) of foraging bats. Its iteration procedure primarily consists of local and global and search stages, and each individual parameters bat i are updated. The solutions for the velocity vector u_i^t and location vector y_i^t in DS-dimensional space and that are updated by exploiting eq. (12) to (14) at the global search phase.

$$ff_i = ff_{min} + \left(ff_{max} - ff_{min}\right)\alpha \tag{12}$$

$$u_i^t = u_i^{t-1} + \left(y_i^{t-1} - y_*\right)ff_i \tag{13}$$

$$y_i^t = y_i^{t-1} + u_i^t \tag{14}$$

In eq. (13), t represent the current iteration number, y_* represent the current global optimum solution and $\alpha \in [0,1]$ represent a random number attained from the uniform distribution. In addition, ff_{max} represent maximum and ff_{min} represents the minimum number of frequencies, correspondingly, which can be produced by the bats. A novel solution y_i^t is created for a bat i at the local search stage if definite circumstances are fulfilled as stated in eq. (15).

$$y_i^t = y'_* + \varepsilon L^t \tag{15}$$

In eq. (15) y'_* represents chosen from between the current best solutions, L^t represents the present average loudness of all the bats and $\varepsilon \in [-1,1]$ represents a uniformly random number. In addition, the present loudness L_i^t and PER (ER_i^t) of bat i can be updated as stated in eq. (16) and (17).

$$L_i^{t+1} = \beta_a L_i^t \tag{16}$$

$$ER_i^t = ER_{max}\left[1 - e^{-\delta_a t}\right] \tag{17}$$

In eq. (17), ER_i^t represents the utmost potential PER and β_a and δ_a represents constants which are usually set to 0.9. Since the iteration number to be inclined as perpetuity, these products are stated in eq. (18).

$$L_i^t = 0, ER_i^t \to ER_{max} \tag{18}$$

4.2 Proposed Enhanced Self Adaptive BA

As same as the prey, a bat maximizes it's PER (ER) when minimizing its loudness L hence it can observe the movement of prey's when remaining are unobserved. Consequently, these modifications in pulse emission rate and loudness considerably have an effect on the search process for optimization. During the initial phases of conventional BA, the L shows an important power; the additional, maximum possible number of global search operations must be carried out. Hence, the probability of the global search for the algorithm must be attuned based on the L. During the final phases of the technique, the pulse ER shows a significantly momentous power; additional, maximum probable amount of global search operations must be carried out. Hence, the local search process must be modified based on the pulse ER. Enthused by these descriptions, this paper developed ESABA by exploiting mutation and step-control method.

a) Step-control method

In the proposed algorithm, the step-control method manages the step sizes which are exploited at each iteration in both the local as well as global searches [15] [16]. The conventional BA exploits the frequency ff to indicate the consequence of modifications in the best solutions for the bat crowd on the velocities, as stated in eq. (13). Nevertheless, the proposed method exploits two frequencies such as ff_1 and ff_2 that indicate the special effects of modifications in optimal solutions for bat group and individual bats, correspondingly, on the velocities. In addition, the two frequencies get used to modifying in both the fitness of bat groups and the iteration process.

Initially, at the global search stage of the proposed algorithm, the novel solutions for the bat i in the DS-dimensional space can be updated by exploited eq. (19) to (22).

$$u_i^t = \eta u_i^{t-1} + ff_1 r_1 \left(g_{i*} - y_i^{t-1}\right) + ff_2 r_2 \left(g_{i*} - y_i^{t-1}\right) \tag{19}$$

$$ff_1 = \beta\left(1 - e^{-\left|FF_{avg} - FF_{best}\right|}\right) + \delta(1-m) + ff_{min} \tag{20}$$

$$A_w = ff_1 + ff_2 \tag{21}$$

$$y_i^t = f y_i^{t-1} + \mu u_i^t \tag{22}$$

In eq. (19), η represents well-thought-out to be a lessening coefficient of weight. It is exploited to provide the method with sturdy global search capabilities on the early stages when lesser η values in the later on stages make sure that the method also shows sturdy local search capabilities. Here, g_{i*} represents the optimal solution for bat i, y^* represents the present global optimum, ff_1 and ff_2 represents the frequencies, and r_1 and r_2 represents the uniformly random numbers haggard from (1.5, 0.5).

In eq. (20), FF_{best} represents the current global optimum fitness and FF_{avg} represents the average fitness of the present optimal solutions for individual bats. Further, $m = t/t_{max}$ represents the estimated index, whereas t_{max} is the maximum number of iterations; so that, $m \in (0, 1]$. At last, ff_{min} represents a constant, which indicates the least value of ff_1. Hence, ff_1 is updated based on the bat group fitness and the present iteration number by the weights β and δ, correspondingly.

Eq. (21) sets the summation of ff_1 and ff_2 to be a constant (A_w), representing that $f_2 = A_w - ff_1$. Since the iteration process continues, ff_1 minimizes from A_w to ff_{min}, when ff_2 maximizes from 0 to $A_w - ff_{min}$. At the initial stages, the high ff_1 values maximize the bat group's diversity as well as enhance the proposed method global search capability, when the high ff_2 values in the ultimate stages assurance the proposed method convergence.

In Eq. (22), μ represent the coefficient of step weight that is exploited to limit the iteration step size. Here, μ is in the range of (0, 1].

Next, the proposed algorithm local search phase exploits a scheme which comprises the pulse ER in the iteration process. If the uniformly random number $\alpha_0 \in [0, ER_{max}]$ is lesser than the ER, bat i achieves a local search by exploiting the eq. (23) and (24). Since ER maximizes as the iteration progress, the probability of the local search is experimental to maximize at the later on stages of the proposed method. This search can be accomplished as stated below if the estimation index $m < 0.4$, subsequently;

$$y_i^t = y'_* + L^t s\gamma \times h(m) \tag{23}$$

Else, if the estimation $m \geq 0.4$

$$y_i^t = y'_* + L^t s\gamma \times 0.1^{h(m)} \tag{24}$$

In eq. (24), L^t represents the bat group's present average loudness, $\gamma \in [-1,1]$ is the uniformly random number, and s represents the distance ratio among the lower and upper as well as lower boundaries of the possible solution domain. The objective model $h(m)$ is exploited to make sure that the high local search paces aid to expand the search domain of the method at its untimely stages when the minimum local search paces in the later stage aid to enhance the search accuracy.

b) Mutation Strategies

The aforesaid step-control strategies can efficiently enhance the global search capability of the method although this capability is still restricted besides the minimizing ff_1 at the later on stages. To further enhance the capability of the method to evade local optima, also the proposed method comprises a mutation strategies which integrates the loudness L. If the uniformly random number $\alpha_1 \in [0,1]$ is lesser than L and bat i have not done a local search, a next random number $\alpha_2 \in [0,1]$ is produced. If this is higher than the mutation threshold $\rho \in [0,1]$, subsequently bat i is rearranged to random values.

Additionally, as stated in eq. (18), L in the conventional BA minimizes to 0 in the subsequent stages, where the pulse ER maximizes to ER_{max}. If the aforesaid values were reserved, the proposed would carry out various local search operations with insignificant step sizes on the subsequent stages, when hardly executing mutation. To additional enhance the competence of the proposed method, it updates L and ER as stated in eq. (25).

$$L_i^{t+1} = \frac{ff_1}{ff_{max}}, ER_i^{t+1} = \frac{ff_2}{ff_{max}} \tag{25}$$

In eq. (25) ff_{max} represents the upper-frequency limit. Based on the fitness of the bat group's and the iteration process ff_1 and ff_2 are adaptively updated. Also, during the search process the proposed L and ER parameters are adaptively changed.

To abridge, this paper presents mutation and step-control mechanisms. By modifying L and ER parameters during the search process, the proposed method efficiently evaded falling into local optima at the premature on stages and has enhanced precision on the subsequent stages.

Algorithm: Pseudo code of the proposed ESABA algorithm		
Initialize the bat algorithm parameters		
Compute the fitness function for all the bats		
Using eq. (20) and (21), update the parameters) ff_1 and ff_2, and update L and ER using eq. (25)		
By eq. (19) and (22), update the location as well as velocity vectors of bat i		
	If $(\alpha_0 < ER_i)$, whereas α_0 is a uniformly random number in $[0, ER_{max}]$, produce a new local solution for bat i by Eq. (23) and (24);	
		If $(\alpha_1 < L_i \mid\mid \alpha_2 < \rho)$, whereas α_1 and α_2 are uniformly random numbers in [0, 1], mutate bat i.
		Compute the fitness group's of the bat, ranked the bats, and update the individual optimal solutions as well as the present global optimum.
If the termination conditions have not been fulfilled, utilize eq. (20) and (21), else, attain the final outcomes.		

5. Experimental Results and Analysis

5.1 Experimental Procedure

The experimentation of the proposed algorithm on the basis of the CHS in IoT-WSN network was performed in MATLAB R2015a and the outcomes were analyzed. The experimentation process of the proposed CHS involves the parameters like delay, distance, nodes energy and temperature and load of IoT devices. In fact, the experimentation was performed by relating to the further parameters with constant values that are exhibited as follows. Moreover, the IoT devices and nodes are allocated within the IoT-WSN network of the area $100m \times 100m$ with BS at center. The ER^I represents the initial network energy that has the value 0.5, where ER^F represents the free space model energy that has $10pJ/bit/m^2$. ER^{DA} represents the data aggregation energy, which is set as $5nJ/bit/signal$. In addition, ER^{PA} represents the power amplifier energy, which is set as $0.0013pJ/bit/m^2$, whereas ER^T represents the transmitter energy, which is set as $50nJ/bit/m^2$. The adaptiveness in proposed CHS was performed for 2000 rounds.

5.2 Performance Evaluation

The efficiency of the proposed algorithm and existing techniques are evaluated in order to find the number of alive nodes remains subsequent to the conclusion of each round that is exhibited in Fig 2. In Fig 2, the proposed method is 21%, 31%, 23% and 25% better than the conventional PSO, GWO, WOA and ABC algorithms for round 2000.

Fig 3 exhibit the performance analysis of the proposed as well as existing CHS models regarding conserving normalized energy for 1 to 2000 rounds. Here, the proposed method is 24% better than PSO, 23% better than GWO, 26% better than WOA, and 27% better than ABC for round 2000.

The temperature of the CHS after the experimentation of proposed and conventional approaches is exhibited in Fig 4. Generally, a reliable CHS technique chooses a node as the CH, if it dispels less temperature. Moreover, Fig 4 exhibits that the proposed method is 16% superior to the PSO, 15% superior to the GWO, 18% superior to the WOA, and 17% superior to the ABC for round 2000. As exhibited in Fig 3, the temperature is appearing to be maximized in a few rounds for the proposed algorithm. Although the temperature is maximum the number of normalized energy and alive nodes, which is exhibited in Fig 2 and 3, are maximum. Hence it is not a problem to choose the nodes that dispel maximum temperature as the CH for the proposed method. Likewise, Fig 5 demonstrates the load of the chosen CH from proposed as well as the existing technique.

The workload of the sensor must be less for obtaining an effectual performance of the network. In Fig 5, the proposed method is 12%, 15%, 13% and 18% better than the conventional PSO, GWO, WOA and ABC algorithms for round 2000. Therefore, a node is chosen as a CH for that the load is lesser. Similarly, the temperature, the load of chosen CH in few rounds might minimize that does not have an effect on the normalized energy.

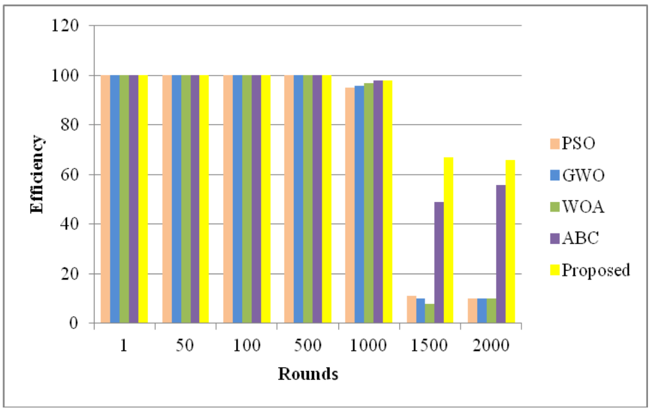

Fig. 2. *Pictorial portrayal of proposed and existing techniques regarding efficiency*

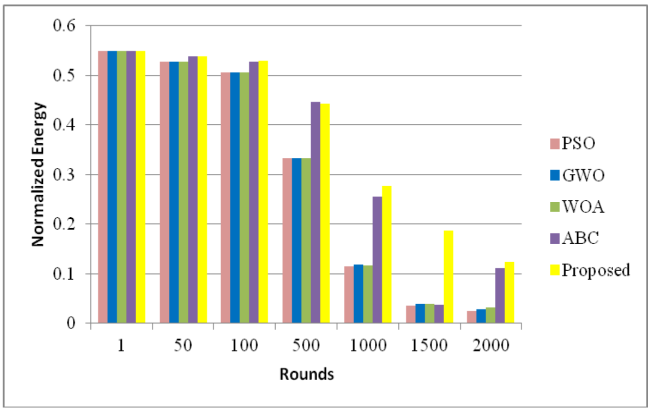

Fig. 3. *Pictorial portrayal of proposed and conventional approaches regarding normalized energy*

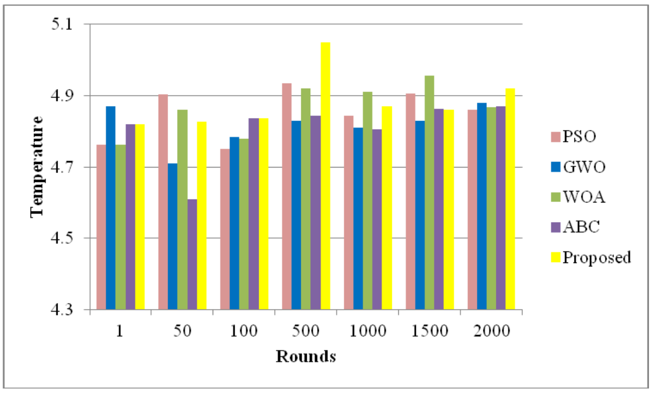

Fig. 4. *Graphical portrayal of proposed and existing techniques regarding temperature*

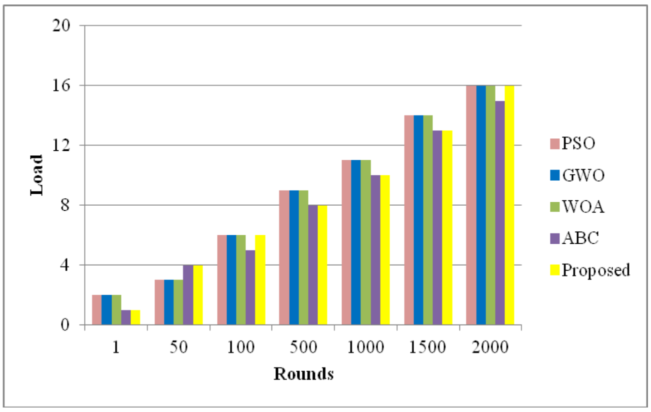

Fig. 5. *Pictorial portrayal of proposed and conventional techniques regarding load*

6. Conclusion

The IoT-WSN main resource is battery power and it always receiving the information and communicating the information to remote location of the IoT network by exploiting this energy only. Hence the energy harvesting is the only solution to keep hold of the lifetime of the sensor network. This paper introduced a novel ESABA approach to propose energy-aware clustering protocols and CHS in IoT-WSN network. The experimentation was performed by considering distance, energy, and SN delay and temperature and load of IoT devices in IoT-WSN network. For the efficiency of the network model, energy of chosen CH must be high and delay as well as distance must below. In IoT devices case, temperature and load of CHS must be least. Moreover, the analysis of performance was performed after creating the experimentation model, by regarding normalized energy, network efficiency, and temperature as well as load of selected CH. For that reason, the proposed method was compared with the existing ABC, PSO, GWO, and WOA techniques.

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