Stabilizing Energy Consumption in Unequal Clusters of Wireless Sensor Networks

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Abstract: In the past few decades, Energy Efficiency (EE) has been a significant challenge in Wireless Sensor Networks (WSNs). WSN requires reduced transmission delay and higher throughput with high quality services, it further pays much attention in increased energy consumption to improve the network lifetime. To collect and transmit data Clustering based routing algorithm is considered as an effective way. Cluster Head (CH) acts as an essential role in network connectivity and perform data transmission and data aggregation, where the energy consumption is superior to non-CH nodes. Conventional clustering approaches attempts to cluster nodes of same size. Moreover, owing to randomly distributed node distribution, a cluster with equal nodes is not an obvious possibility to reduce the energy consumption. To resolve this issue, this paper provides a novel, Balanced-Imbalanced Cluster Algorithm (B-IBCA) with a Stabilized Boltzmann Approach (SBA) that attempts to balance the energy dissipation across uneven clusters in WSNs. B-IBCA utilizes stabilizing logic to maintain the consistency of energy consumption among sensor nodes'. So as to handle the changing topological characteristics of sensor nodes, this stability based Boltzmann estimation algorithm allocates proper radius amongst the sensor nodes. The simulation shows that the proposed B-IBCA outperforms effectually over other approaches in terms of energy efficiency, lifetime, network stability, average residual energy and so on.

Keywords: WSN, stability, cluster head, node balancing, average residual energy.

1 Introduction

With constant progression in wireless communications, Internet of Things (IoT) finds its applications over several WSN applications like smart city, traffic control, health care, environmental monitoring and disaster monitoring. In order to recognize the environmental conditions in certain region, huge amount of Sensor Nodes (SNs) are deployed [Zhang, Li, Zheng et al. (2014)]. The SN report the Base Station (BS) periodically, if an event is encountered. BS acts as a gateway amongst sensor node, where user(s) attain needed

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information from BS via Internet [Albaladejo, Snchez, Iborra et al. (2010)].

In general, SNs are small sized devices and economically cheap with smaller memory; therefore, their power and energy are extremely limited [Amini, Vahdatpour, Xu et al. (2012)]. As well, SNs are dissolved completely, where its accessibility accessibly is restricted to users and such SNs are impossible to substitute node battery. Henceforth, EE of SNs is crucial to lifetime [Baranidharan and Santhi (2016)]. In contrast with transmission, other overheads are relatively lesser. This is considered as a choice of the routing protocols, however it makes the entire process to be complex [Cengiz and Dag (2018)]. Based on literature, numerous clustering algorithms are anticipated.

So as to prevail over this enormous energy for undeviating BS transmission, cluster based transmission protocols are extremely investigated and utilized [Cuevas-Martinez, Yuste-Delgado and Triviño-Cabrera (2017)]. WSNs are partitioned into cluster group, where each cluster group comprises of coordinators or CH. Data collected from Cluster Member (CM) is not directly sent to BS, but forwarded to CH [Belabed and Bouallegue (2016)]. In general, responsibilities of CHs involve data aggregation which forwards to BS from CMs.

Certain routing algorithms reduces the energy dissipation and it further enhances the network lifetime. Depending on the existing approaches, LEACH applies random CH selection model and constantly changes the role of CHs to maintain energy consumption [Harb, Makhoul, Tawbi et al. (2017)]. EAMR approach constructs cluster similar to LEACH with slight EAMR modification. It uses multi-hop routing, fixed clustering and threshold based CH selection approach [Hoang, Yadav, Kumar et al. (2014)]. An imp-K-means is based on K-means as baseline that uses equal clustering model to place the clusters [Kumar and Hegde (2015)]. EAUCF operates on a probabilistic model to choose the CHs and that benefits over fuzzy logic to assign radius [Ren, Zhang, Zhang et al. (2015)]. DFCR is anticipated to resolve hot spot crisis [Otoum, Kantarci and Mouftah (2018)]. It considers neighborhood density, energy, transmission cost and distance as primary cause for cluster radius computation and CH selection [Singh and Lobiyal (2012); Tam, Hai, Son et al. (2018)].

In this work, we anticipate a novel Balanced-Imbalanced Cluster Algorithm (B-IBCA) with Stabilized Boltzmann Approach (SBA) to unequal network connectivity (unequal cluster). Apart from existing CH selection approach, B-IBCA based SBA focuses over BS distance and average residual energy of nodes, and employs Boltzmann model to stabilize energy consumption to determine the priority of node for handling the CHs. In accordance with the information on cluster nodes, B-IBCA determines cluster radius adaptively. After cluster formation, B-IBCA uses hop routing protocol. CH propagates data amongst clusters via relay, and at last transmits to BS as in Fig. 1. This model gradually diminishes SNs energy overhead and that increases lifetime eventually.

To analyze performance of anticipated algorithm, B-IBCA is compared with existing LEACH, K-means and DFCR. Simulation is performed under various scenarios and the outcomes depicts that B-IBCA operates effectually than existing algorithms in energy efficiency, lifetime and stability.

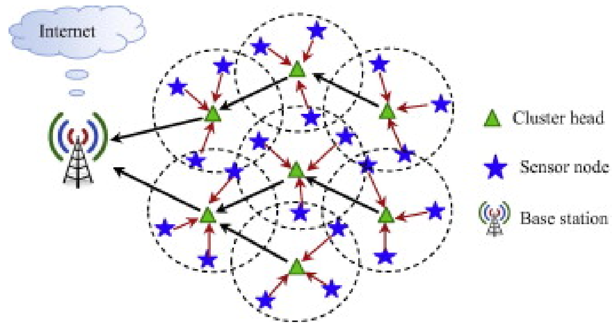

Figure 1: Clustering in WSNs

The work is structured as: In Section II, works associated to clustering based routing algorithms encountered is briefly given. In Section III, network model, energy model and proposed B-IBCA with SBA is discussed. In Section IV, simulation set along with numerical results and corresponding discussions are done. The anticipated model is compared with existing LEACH, K-means to evaluate the results more effectually. At last, conclusion and future works are illustrated in Section V.

2 Related works

This section discusses about previous investigational works based on energy replacement, agent based routing, and energy aware routing and machine learning based energy computation. The research gaps are analyzed and optimal solution is provided for further enhancements.

2.1 Energy replacement

In Yi et al. [Yi, Deng and Liu (2012)], Anticipated procedures for charging vehicles, modelled to renovate nodes lifetime. This protocol is accountable to acquire status of node precisely. In Singh et al. [Singh and Lobiyal (2012)], depicted that deployment of vehicle to accumulate data from every node simultaneously. Moreover, time for charging accumulative nodes with gathering time may leads to reduced network delay.

Hoang et al. [Hoang, Yadav, Kumar et al. (2014)] demonstrated that charging vehicle is not sufficient to protect lifetime and it manages every sensor node with charging vehicle. In Cengiz et al. [Cengiz and Dag (2018)], the author specifically discards WPT approach for dynamic routing with proper charging cycles with an idea of ESync to diminish delay using travelling salesman problem.

2.2 Energy-aware data routing

Usually, Reinforcement Learning (RL) is a training approach from online learning machine learning category. RL facilitates to attain experience from environmental conditions for resolving previous mentioned crisis like data routing, data rate and energy conservation. In Wang et al. [Wang, Liao, Cao et al. (2014)], anticipated topology control algorithm with Q-learning approach and SNs are preserved via k-degrees. Nodes share information of power transmission and range between them to preserve energy consumption.

In Abbasi et al. [Abbasi and Younis (2007)], charging cycle is initiated to optimize routing. In addition, recharging path for wireless charger gets reduced with decrease in charging delay along with energy conservation and localization is performed through reinforcement learning.

Most prevailing routing approaches are modelled for diminishing the energy consumption devoid of measuring the fair allocation. Indeed of previous works, the anticipated paradigm significantly resolves the routing strategy. The anticipated routing model termed as C-SARSA diminishes the consumption of energy and assists it to improve the stability between sensor nodes.

2.3 Agent based routing

In general, solutions of agent sourced routing to resolve crisis increases with basic characteristics. Outcomes are generally provided for aggregation, effectual route estimation, reconfiguration crisis, programming concept. The foremost predominant resource sharing agent in existing work is sensor ware and agilla. Subsequently, agent sourced solutions are based on technology, and constraints like NoBV are accessible in those solutions.

2.4 WSNs middleware

In Zhang et al. [Zhang, Das and Liu (2006)], initiated mobile agent middleware termed Eagilla i.e., in co-operation with WSN for sensing the data. This structure offers flexibility and scalability to network. The agent is accountable for communication and functions as a mobility part to move over network and adopt based on tasks. SNs in network functions as CH and then as agent sourced on CH functionalities. Further the network scalability and applications are enhanced and managed by CH indeed of base station. There are three kinds of sensor nodes; client, server and nodes. Free nodes functions as independent nodes and merge cluster. Server nodes are CH that makes communication to and from base station. At last, client nodes possess communication authority with CH. This structure increases network connectivity.

2.5 Machine learning in WSNs

In recent times, Machine learning based Middleware (MaML) handled the crisis of ontology heterogeneity. Moreover, potential crisis in MaML is overhead. Dynamic characteristics of WSN are constantly optimized owing to system design requirements [Yi, Deng and Liu (2012)]. So as to eliminate necessity of an unessential network redesign, various machine learning approaches are applied in WSNs. Designers of SNs determine ML as an algorithm and accumulate tool that is cast off to recognize prediction models. ML enhances resource utilization, allocation and delegation as an effort to extend network lifetime. ML utilizes mathematical modelling that is sourced on statistical approaches for artificial intelligence based data sampling [Zhang, Li, Zheng et al. (2014)]. It adapts and learns to constantly changing circumstances. Interfacing approaches in ML acts as an essential function in WSN applications. ML interfacing is performed in three phases: data processing, data aggregation and interfacing. These steps are cast off for modelling and observing dynamic environments related to WSNs.

With the baseline of existing methods and related suggestions, it is depicted that most prevailing middleware models do not offer comprehensive system to deal enormous data and transmission amongst sensors and base station securely. As data is extremely prone to attack while the time of transmission, robust approach that not only offers secure communication, however improves network efficiency when needed [Zhou, Cao, Chen et al. (2009)]. This method has developed an approach based on machine learning that creates bogus data to guarantee communication amongst BS and SNs by deceiving attackers. This approach removes the essentiality to produce bogus packets or nodes for security and diminishes power consumption; thereby enhancing the throughput and delay.

3 Proposed model

This section depicts network modelling applied in this work, where the network model assumptions related to this study is given below:

3.1 Network model

- All SNs are deployed randomly in target zone, after deployment process, both BSs and SNs remains stationary.
- All SNs knew its location obviously after deployment process.
- All SNs possess the competency to alter its transmission power in accordance to nodes distance.
- Initial energy of all SNs is same.
- Energy supply and processing power of BS are infinite.

3.2 Energy model

In simulation environment, energy consumption from nodes or energy dissipation uses first order radio model. Eq. (1) specifies energy while transmitting ‘n’ data to distance ‘d’.

$$E_{tnx}\,(n,d) = \begin{cases} nE_d + n \in_{fs} d^2 & d < d_0 \\ nE_d + n \in_{mp} d^4 & d \geq d_0 \end{cases} \tag{1}$$

Eq. (2) specifies energy consumed while receiving ‘n’ data bits.

$$E_{rnx}\,(n,d) = nE_{tnx+rnx} \tag{2}$$

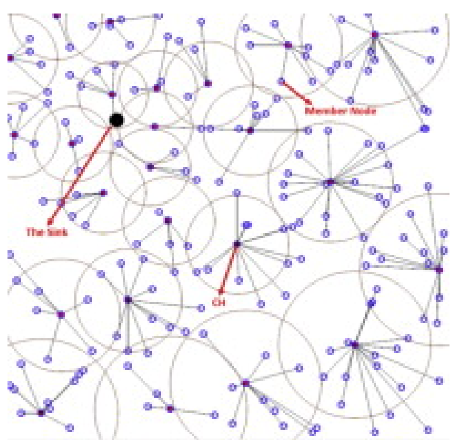

Figure 2: E-U clustering

Based on above expression, 'n' specifies sum of transmitted bits, 'd' specifies distance amongst transmitter/receiver, 'd_0' specifies threshold over transmission distance, $E_{(tnx+rnx)}$ specifies energy consumed while transmission and reception is carried out in sensor circuitry. If distance amongst transmitter/receiver is smaller than threshold d_0, ϵ_{fs} specifies energy dissipated in free space, else, ϵ_{mp} specifies multi-path model. The value of d_0 is generally computed as in Eq. (3):

$$d_0 = \sqrt{\frac{\epsilon_{fs}}{\epsilon_{mp}}} \quad (3)$$

By considering the correlation amongst nodes' data nearer, CH uses data aggregation. This is to aggregate data to diminish data redundancy. Considering global time synchronization, data aggregation model can effectually diminish network traffic; however it increases the network delay during transmission. Data aggregation is partitioned to Rising Aggregation (RA) and constant aggregation based on size of aggregated data packet. This investigation utilizes RA model. CH node constructs smaller data packets length in accordance to certain ratio. Aggregated data length is computed based on Eq. (4):

$$L_{DA} = L_r + L_r * \varepsilon * N \quad (4)$$

Here, L_{DA} specifies the length of aggregated data packet, L_r specifies data packet, $\varepsilon(0 \leq \varepsilon \leq 1)$ specifies aggregation ratio and 'N' specifies number of CHs.

Energy utilization while aggregation process is specified as E_{DA}. In precise, energy dissipated over CH node is specified with Eq. (5):

$$E_{CH} = E_{tnx} + E_{rnx} + E_{DA} \quad (5)$$

$$E_{nCH} = E_{tnx} \quad (6)$$

Energy consumption model based on CH and non CH is provided below as in Eqs. (5) and (6).

3.3 Problem formulation

Let $'N_{LT}'$ specifies lifetime, T_{h-h} and T_{tnx} specifies total amount of H2H and total amount of transmission provided by nodes correspondingly, while T_rnx specifies total amount of reception by node in network lifetime as in Eqs. (7) and (8):

$$E_{n-rnx} = T_{rnx}E_{tnx-rnx} \quad (7)$$

$$E_{n-tnx} = T_{tnx}E_{tnx_{sn}} + T_{h-h}E\_tnx_{ht} \quad (8)$$

where, $T_{h-h} = S_n + F_n$; S_n specifies total transmission to successor node, $F_n$specifies total transmission to facilitating node. $E_{tnx-rnx}$ denotes energy consumed by SN to receive packets, $E_{tnx_{sn}}$ denotes energy consumed during transmission towards sink. E_tnx_{ht} specifies energy consumed during transmission of packet to certain region as in Eq. (9):

$$E_n = T_{tnx}E_{tnx_{sn}} + T_{rnx}E_{tnx-rnx} + S_n\, E_{tnx_{sn}} + F_{n\, E_{tnx-rnx}} \quad (9)$$

Energy computation is done by Eqs. (10)-(12):

$$\left\{\min(\textstyle\sum_{S_j \in \theta} \sum_{i=1}^{C(S_j)} E_{ij}) \right. \quad (10)$$

$$\left\{\min E_{S_j} \approx E_{S_{j+1}} \right. \quad (11)$$

$\{\min \ E_{ij} \ \leq E_0$ (12)

The ultimate objective is to reduce energy consumption during transmission in SN. These constraints ensure that energy is minimized during overall energy consumption on network that is unequal.

1. How to balance unequal cluster based energy consumption amongst nodes in network connectivity?
2. How to balance unequal cluster nodes in certain network range?
3. How to determine threshold value of cluster in transmission range?
4. How to maintain connectivity over large time period?

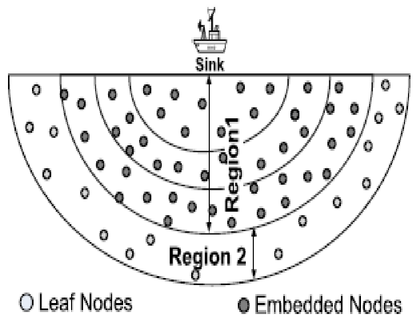

Figure 3: Nodes of WSNs

3.4 Solution

Here, the anticipated B-IBCA algorithm is described in detail. The proposed B-IBCA is a randomly distributed unequal clustering algorithm for balancing energy dissipation. So as to describe nodes priority for electing CH, B-IBCA is modelled based on stabilized Boltzmann Approach (SBA) which measures the cluster energy and distance of various cluster connectivity to BS. However, B-IBCA uses energetic visible and hidden layers in an unsupervised manner to allocate cluster radius in accordance with local cluster node condition after each iteration. After modelling equal and unequal clusters, routing network is provided to carry out transmission. B-IBCA comprises of subsequent phases: CH determination, Equal-Unequal (E-U) radius computation, cluster arrangement and routing process.

3.5 CH determination

After SNs deployment every node is positioned in own location. In general, BS periodically transmits message that includes BS location and BS id. After BS message, node (i) stores BS-id and BS-location information, it computes distance to BS as in Eq. (14):

$$D_{BS}(S_i) = \sqrt{(A_i - A_{BS})^2 + (B_i - B_{BS})^2} \quad (13)$$

If SNs are closer toward BS, it exhibits superior facility in the direction of participating with CH and higher possibility on turning to devices. As well, it is clear that nodes' energy is correlated positively with capacity to CH competency. Henceforth; B-IBCA uses both BS distance and residual energy to describe every node priority for CH as in Fig. 3. Uncertainty in CH competition is dealt by Boltzmann model over hidden and visible layer for energetic modelling. The probability of cluster formation with essential configuration, energy function, network score uses visible element and allocate probability of unequal clustering is done with Boltzmann approach.

3.6 Cluster radius calculation

Equal-Unequal radius computation

Here, Equal-Unequal radius computation is crucial to compute network lifetime. For evaluating Equal and Unequal cluster radius, significant parameters have to be considered and determined as below:

3.6.1 Equal-unequal cluster node density

Consider a local network region, where SNs are randomly distributed and Equal-Unequal cluster node radius has to be minimize to diminish CH nodes' energy consumption and facilitating it to dissolve quickly. On contrary, in local region where SNs are distributed sparsely, Equal-Unequal cluster radius is expanded suitably. Node broadcasts SN message with fixed radius, comprising nodes' location and nodes' ID. As the neighborhood node receives broadcast message, it will provide an ACK message with node ID, residual energy and node location. After that, node stores neighborhood node information in location with neighbor list. It is revised in accordance to present neighbors at every round. Neighborhood node density (node degree) is evaluated with Eq. (14), where 'N' specifies number of all SNs in WSNs.

$$D_{E-U}\ (i) = \frac{|E-U(Neighbor(i)|}{N} \tag{14}$$

3.6.2 Neighborhood distribution

Neighborhood data distribution influences cluster size radius. It is considered as another representation of Equal-Unequal distance. Neighborhood distribution is evaluated with Eq. (15):

$$Neighbourhood_{E-U\ distribution\ (i)} = \sum_{j \in Neighbourhood\ (i)} \exp(-Dist\,\frac{(s_i,s_j)^2}{2\sigma^2}) \tag{15}$$

where, 'σ' specifies SD of ordinate and abscissa neighborhood values in $S(i)$.

CH energy distribution for transmitting packets is correlated with CH distance, it specifies that distribution amongst E-U clusters are relatively discrete, CH has to use energy to broadcast packets to CH. Henceforth, radius has to be reduced suitably to decrease intra-cluster energy dissipation. In contrast, node distribution is relatively focused by increasing the radius.

3.6.3 E-U residual Energy

If radius is higher, energy is more in CH node, recognizes that it is simple. When network usage is higher, energy is constantly dissipated, outcomes in reduction of cluster radius. Relative residual energy of E-U clusters, that is, E_RRis provided as E_R (i).E_i (i). Neighborhood nodes have similar features. Therefore, if neighborhood region possess average relative residual energy, network region possess larger cluster radius.

3.6.4 Distance to BS

Assume WSN based hotspot problem, CH nodes that are nearer to BS will encounters higher data traffic, that causes earlier dissolving condition of CHs. Henceforth, regions nearer to BS reduces cluster radius that can decreases CH load drastically. Consider, sensor deployment region is in rectangular region. As depicted in Fig. 3. region far away from BS comprises four region of vertices, that is, (0, 0), (A, 0), (0, B) and (A, B) respectively.

BS relative distance is evaluated using Eq. (16):

$$D_{BS}(i) = \frac{D_{BS}(i)}{\max(d_1,d_2,d_3,d_4)} \tag{16}$$

Based on above parameters, B-IBAC computes adaptive cluster radius sourced on nearer neighborhood node conditions.

3.6.5 E-U Boltzmann approach

Here, E-U Boltzmann approach is neural; stabilizing network with two layers: Hidden (H) and Visible (V). Stabilizing procedure is managed using unsupervised manner. E-U Boltzmann facilitates connections amongst neurons of diverse clustering without any restrictions. In E-U, 'W' specifies weights amongst hidden and visible layers, W_{AB} specifies weight of both visible V_A and hidden H_B units. E-U energy function is depicted in Eq. (17):

$$E(V_A, H_B|\theta) = -\sum_{a=1}^{A} x_a V_a - \sum_{b=1}^{B} y_b H_a - \sum_{a=1}^{A}\sum_{b=1}^{B} V_a H_b W_{ab} \tag{17}$$

Here, W_{ab}, x_a, y_b specifies E-U parameters, V_a and H_a specifies visible and hidden biases, 'A' and 'B' specifies number of equal and unequal clusters.

(V, H) probability formulation is provided in Eq. (18):

$$P(V,H) = e^{-E(V,H)} / \sum_{A,B} e^{-B(V,H)} \tag{18}$$

where, $e^{-B(V,H)}$ specifies normalization that specifies all probable network configurations, with equal and unequal cluster elements. With energy function, network facilitates probability score to various cluster scenario in visible and hidden elements. Probability assigned to visible element 'V' is given in Eq. (19):

$$P(V) = \sum_B P(V,H) = \frac{\sum_B e^{-E(V,H)}}{\sum_A \sum_B e^{-E(V,H)}} \tag{19}$$

Similarly, probability assigned to unequal element 'H' is provided in Eq. (20):

$$P\,(H) = \sum_A P\,(V,H) = \frac{\sum_A e^{-E(V,H)}}{\sum_A \sum_B e^{-E\,(V,H)}} \tag{20}$$

Here, E-U comprises of 'N' clusters with 'N' SNs in every cluster. In every cluster, CH is accountable for transmitting sensor data directly to BS; that is in central server. Aggregated data then undergoes energy computation namely, Stabilitized Boltzmann Approach (SBA).

Using SBA, with B-IBCA, CH selection approach is achieved with weighted CH determination process, which computes weight of every SN and evaluates weight with other nodes (weight specifies equal and unequal cluster nodes). With this approach, every sensor is provided with $'W_n'$ which nodes function (degree, mobility and received signal strength) is. After evaluating weight, node shares ID number, then measures it weight with adjacent nodes like SN. CH is node that attains lowest $'W_n'$. This CH determination process moves through Algorithm 1.

In E-U Boltzmann approach and SBA, every CH evaluates data from sensors with stabilized cluster, and transmits by adjusting aggregation process. This evaluates aggregator score sourced on sensor trust values and evaluation amongst aggregator and sensors.

In Eq. (20), T_{CH} specifies trusted score of aggregator CH. $'T_n'$ specifies 'n' nodes trust score and $'T_n'CH$ specifies CH trust evaluation and sensor node 'n'.

$$T_{CH} = \left(\sum_{n=0}^{n-1}(T_n + 1).T_{CH}^n\right)/\sum_{n=0}^{n-1}(T_n + 1)) \qquad (20)$$

With E-U Boltzmann approach and SBA, this approach comprises of nodes that contain 'n' visible nodes, like $(V_1, V_2, \ldots, V_x)$ unequal layers and output energy utilization.

Algorithm 1:

Procedure: CH determination with E-U Boltzmann approach using SBA

Input: d_n, RSS, node mobility M_n

Output: W_n

For every Equal and Unequal node 'n' do

d_n → neighborhood SN with E-U cluster

δ → CH and node density

Δ_n→ differences between equal and unequal clusters

RSS_n;

Total RSS received;

Stabilizing sum of RSS;

M_n → mobility of Equal and Unequal clusters to BS

W_n → combined nodes weight in Equal and Unequal clusters

End for

Return W_n

Chose node with minimum W_n as CH

Eliminate CH determination from nodes set

Repeat step for all nodes in cluster

End

End procedure

4 Numerical results and discussion

In this section, several experimentations have been done to perform anticipated algorithm B-IBCA. Simulation has been performed in MATLAB 2016. Based on the influence of BS location, diverse network scenarios were considered. In Case 1, BS is positioned at ROI and in Case 2, BS is located at center of ROI. Coverage region is 100 m×100 m, total amount of nodes in WSNs are 200. Figs. 4 and 5. explains these two cases.

In simulation environment, networks run in various rounds. Every round is partitioned into four stages in accordance to anticipated B-IBCA with SBA model: CH determination, Equal-Unequal (E-U) radius computation, cluster arrangement and routing. Clustering features utilized for comparison are depicted in Tab. 1. Such as LEACH, K-means, DFCR respectively.

Table 1: Simulation setup

Parameters	Value
Area	100×100
BS	0-50 m
Total sensors	200
Energy	0.5 J
Packet size	500 bytes
Delay	20 s
Cluster radius	20 m
Aggregation ratio	20%
Aggregated energy	5 nJ/bit
fs	10 pJ/bit/m2
mp	0.0013 pJ/bit/m4
Parameters	Value

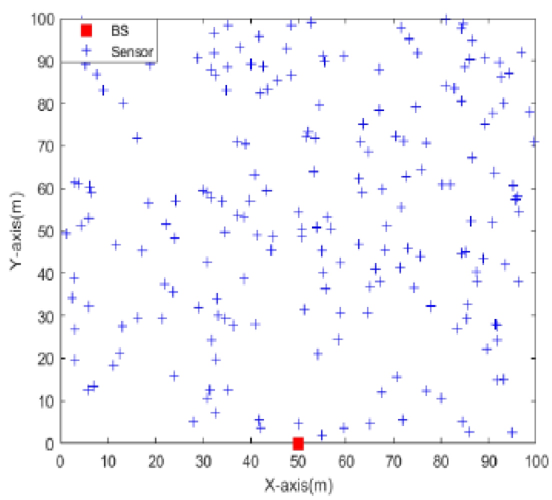

Figure 4: Equal node clustering

4.1 Energy efficiency

The SN energy is crucial constraints of WSNs, where the consumption of SNs are typically based on routing protocol. Power consumption of equal and unequal clusters specifies entire network lifetime that will stabilizes network enhancement. Average residual energy of the proposed model with existing nodes per round is contrasted with DFCR and K-means respectively.

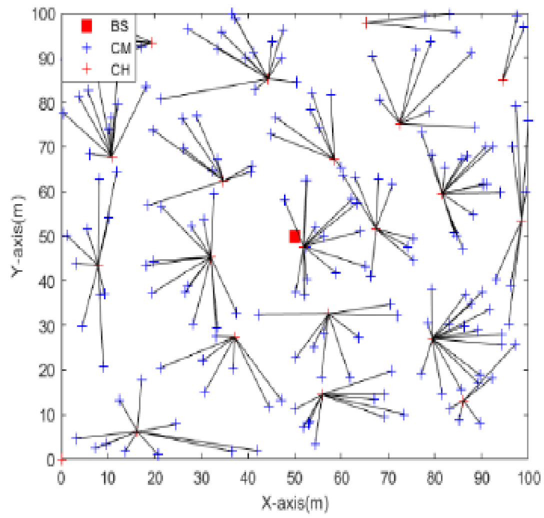

Figure 5: Unequal node clustering

As depicted in Fig. 5, B-IBCA is energy efficient algorithm for cases 1 and 2. Henceforth, B-IBCA has superior network stability. For LEACH, K-means and DFCR due to its stochastic approach for CH determination, low energy nodes is chosen as CHs. K-means uses clustering method, which is not effectually diminish energy in non-uniformly distributed cases as in Fig. 6. As well, for LEACH, k-means, clustering generation strategy considers distance from non-CH to CH and CH energy, while eliminating cluster size optimization. Henceforth, it can effectually stabilize CH energy dissipation.

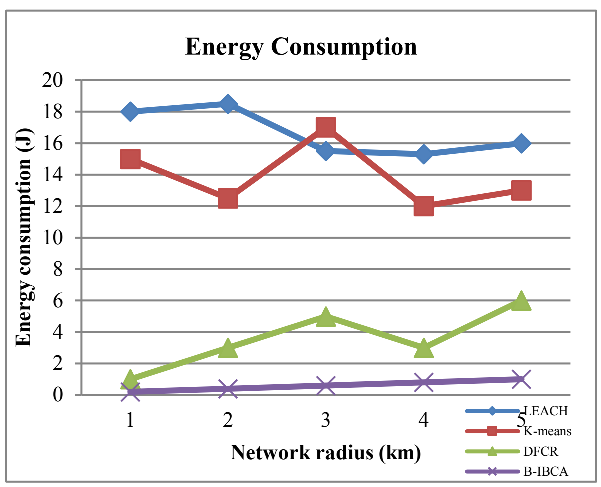

Figure 6: Energy consumption

Following steps shows that energy efficiency of proposed model is more effectual than other algorithms.

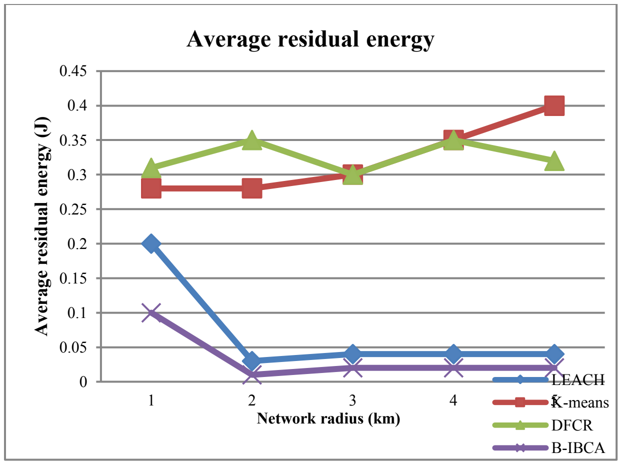

Figure 7: Average residual energy

B-IBCA merits are given below:

● In B-IBCA, higher energy nodes are closer to BS and possess superior priority of CH determination by eliminating low energy nodes deficiency specifically in randomly distributed CH as in Fig. 7.

● B-IBCA is naturally distributive, demonstrating superior performance in network stability and scalability.

● In contrast to other clustering algorithms, B-IBCA does not need to set up higher threshold value alike of other clustering algorithms, thus diminishing influences of human experience as in Fig. 8. B-IBCA determines dynamic modification with node information, adaptively describes radius in accordance to network environment.

● In cluster formation, non-CH select to merge cluster like LEACH. Moreover, B-IBCA considers distance from CH to BS, distance from non-CH to CH, CH energy and CH to BS direction, optimize CH.

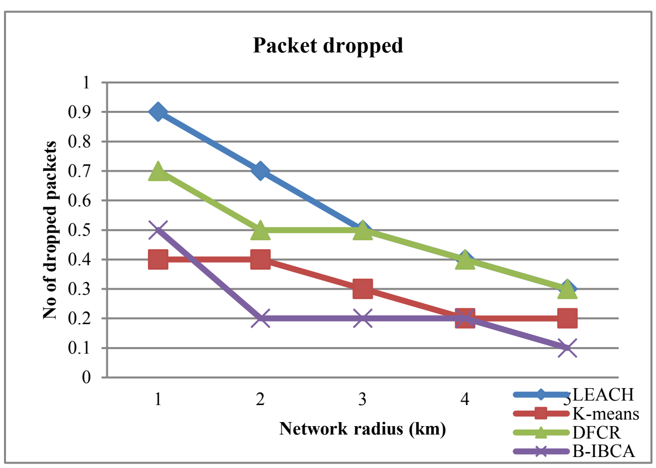

Figure 8: Packet dropped

5 Conclusion

In this paper, a novel B-IBAC is designed to stabilize the loads of equal and unequal clusters amongst all SNs. B-IBAC comprises of four phases: Equal-Unequal (E-U) radius computation, cluster arrangement and routing process that dynamically modifies the sensor node condition. B-IBAC allocates the required radius of clusters to SNs using SBA. From CH determination and computation of cluster radius, the proposed B-IBAC tends to eliminates well the random uncertainty effects. The proposed method is effective in its energy efficiency and increasing the network lifetime in contrast with K-means, LEACH, and DFCR algorithms. Experimental validation shows that the proposed B-IBAC is consistent and balances well the energy efficiency. In future, a stabilized Boltzmann approach is considered to elect region of interest and the use of active CH may enhances the network lifetime.

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