Turkish Journal of Engineering
https://dergipark.org.tr/en/pub/tuje
e-ISSN 2587-1366

Energy capable protocol for heterogeneous blue brain network

Rajesh Dennison *1, **Giji Kiruba Dasebenezer** 2, **Ramesh Dennison** 3

1 Vel Tech Rangarajan Dr. Sagunthala R&D Institute of Science and Technology, Department of Computer Science & Engineering, India, rajeshd936@gmail.com
2 Satyam College of Engineering and Technology, Department of Electrical and Electronics Engineering, India, d.jijikiruba@gmail.com
3 Anna University, Department of Computer Science and Engineering, India, ramesh4773@gmail.com

Cite this study: Dennison, R., Dasebenezer, G. K., & Dennison, R. (2024). Energy capable protocol for heterogeneous blue brain network. Turkish Journal of Engineering, 8 (1), 152-161

Keywords
Blue Brain
Broadcasting
Energy
Cutoff
Heterogeneous network

Research Article
DOI: 10.31127/tuje.1346925

Received:20.08.2023
Revised: 22.11.2023
Accepted:24.11.2023
Published:15.01.2024

Abstract

The Blue Brain has a wide range of applications, which raises a number of challenging issues. Electronics may continuously monitor their surroundings depending on the real data that their Blue Brain nodes are acquiring by employing situational intelligence based on the Blue Brain environment. The Blue Brain does more than only monitor user behavior when utilizing this technology. Blue Brain is linked to a critical prerequisite for energy-efficient communication methodologies. Through the Blue Brain network, it utilizes the heterogeneity and variety of the interconnected components. Blue Brain nodes that are outsourced and have limited energy resources must utilize less energy. IoT nodes with differing energy levels are frequently dispersed across different geographic regions. The main goal of this work is to provide an energy-efficient Blue Brain framework capable of managing cluster head (CH) selection and Blue Brain node clustering. The appropriate CHs are selected, and an energetic cutoff concept is developed to guarantee that energy is shared equally among the CHs and participating Blue Brain nodes. The proposed concept envisions three different kinds of Blue Brain nodes for a Blue Brain infrastructure: expert, intermediary, and normal Blue Brain nodes. Level 1 Blue Brain nodes are regarded as normal nodes; level 2 nodes are regarded as intermediate Blue Brain nodes; and level 3 nodes are regarded as expert Blue Brain nodes. Level 1 Blue Brain nodes use the least amount of energy. The outcomes of the simulation demonstrate that the recommended strategy outperforms other existing methods.

1. Introduction

Over the past ten years, there has been a notable increase in the everyday use of digital gadgets. The "internet of things" (IoT) enables connections between cellular applications, RFID tags, workstations, sensors, and other objects in the environment [1-4]. IoT technology allows these devices to monitor their environment closely and provides situational awareness by using data collected in real time by its Blue Brain nodes.

The Blue Brain not only oversees the products but also monitors the behavior of its owners. Blue Brain is being used more and more in a variety of applications, such as smart home design, health analysis, and environmental observation [5-8]. As such, increasing the effectiveness of real information gathering and communication is a challenging undertaking.

The following categories can be used to group issues about Blue Brain nodes. First, consistency. The networks bottom layer is actually responsible for ensuring Blue Brain's accuracy; the network layer-routing algorithm must address this problem. One approach is to retransmit information packets, although this increases data transmission delay and slows down efficiency [9]. The second difficulty is the cumulative real-time performance of the Blue Brain networks.

Assuring that any transport system can provide a high degree of resilience with every network Blue Brain node alive and reachable for communication is the final worry [10]. The approach has to decrease the number of CHs because Blue Brain nodes have limited processing and battery life [11–13]. It is necessary to consider each of these issues while developing a new routing method. Real-time environmental monitoring creates another obstacle for the Blue Brain. The Blue Brain nodes might be dispersed throughout many locations. Figure 1 shows the several Blue Brain nodes that can be employed in different scenarios. While such Blue Brains are always monitoring their surroundings, they may not have much discretion when it comes to battery replacement. As a result, numerous researchers have concentrated on improving the functionality of these Blue Brain nodes by reducing their energy consumption. Furthermore, a number of methods have been developed to lower energy usage and communication latency [14,15].

A lot of specialists think that clustering can lower a Blue Brain networks energy consumption. in the name suggests, Blue Brain nodes are grouped together in clusters. Every cluster selects a CH who will collect information from some of the other cluster members and forward it to a Blue Brain node that serves as a sink. The CH is therefore essential for managing the amount of energy utilized. The current clustering techniques are not able to minimize the overall energy usage of large Blue Brain networks. Figure 2 shows a potential heterogeneous network somewhere at the point of beginning with varying energy levels. Groups of Blue Brain nodes with the lowest energy use are referred to as "regular" Blue Brain nodes. The 'intermediary' Blue Brain nodes use energy in a range between these two, whereas the 'expert' Blue Brain nodes have the highest energy needs.

In this research, concentrates on creating a methodology for reducing Blue Brain node energy utilization and extending system lifetime [16].

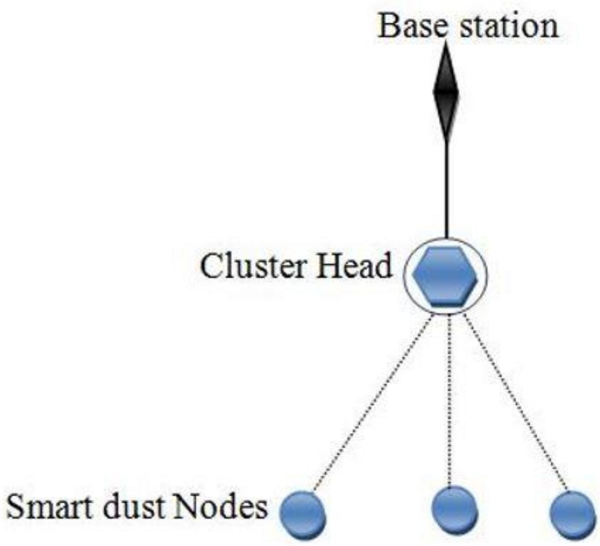

Figure 1. Blue brain architecture.

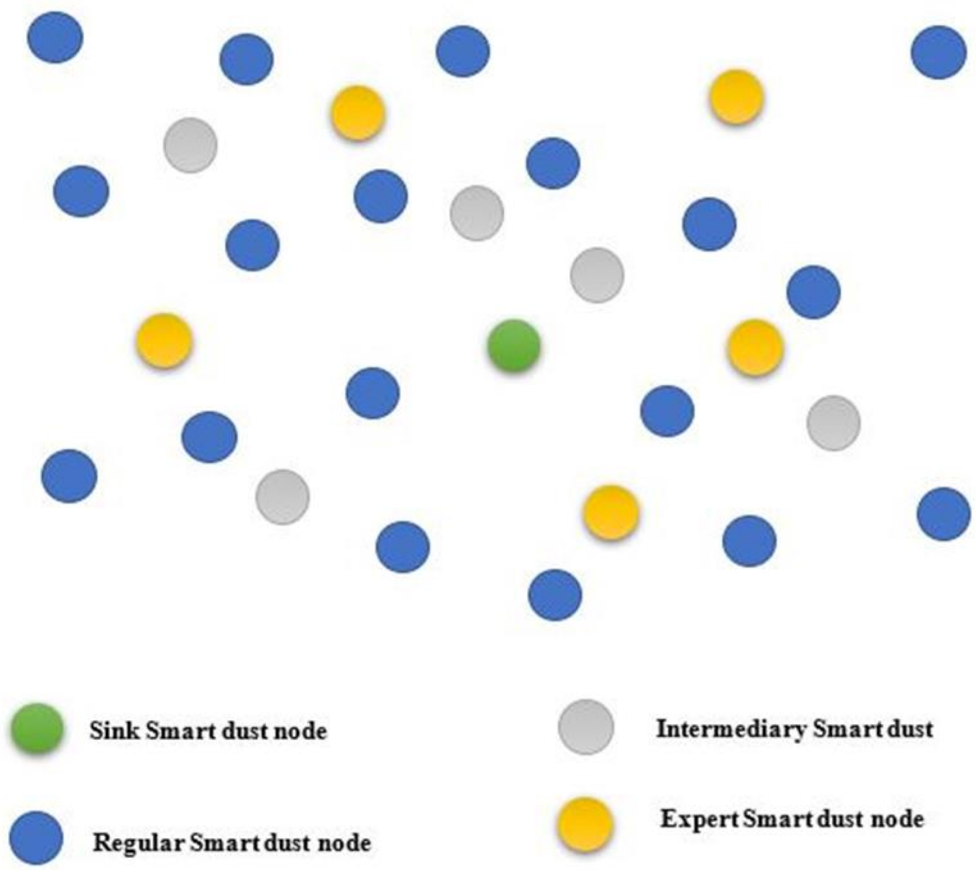

Figure 2. Proposed heterogeneous network architecture.

For the past ten years, researchers have concentrated on developing a real-time information transmission system across the Blue Brain. Most of the discussion has focused on data transmission energy use. The LEACH method, which selects the CH at random, was developed by the authors of [17]. Therefore, every Blue Brain node in the network has an opportunity to be selected as the CH during the 1/p timestamp. In further cycles, an arbitrary number between 0 and 1 is acquired at arbitrary [18]. The CH will be a Blue Brain node with energy intensity below the threshold [19]. The next CH is determined by grouping non-CH Blue Brain nodes. Only once the cluster has formed does the CH notify the associated nodes via ADV. The nodes transfer this data to

CH during the allotted time-division multiple access (TDMA) session. The primary drawback of the LEACH methodology is its inapplicability non situations involving extensive detection. In a heterogeneous network, certain progressive nodes use more energy than standard nodes [20]. The weighted possibilities are used in the stable election process (SEP) method to select the CHs. It has the advantage of greater consistency and efficiency over the LEACH methodology. A hybrid strategy known as the zonal stable election process (Z-SEP) methodology is recommended by the researchers of [21].

The Z-SEP is divided into three regions: 0, 1, and 2. In Region 0, the nodes are placed in an arbitrary manner. These progressive nodes, which consume a lot of energy, are distributed randomly and equally throughout regions 1 and 2. The Z-SEP uses two distinct broadcasting techniques to provide data to the base station (BS). The first sensor nodes immediately transmit data to the base station. Second, after receiving the data from the sensor nodes, the cluster head sent it to the BS. The CH selected for each cycle is determined by the cutoff value.

2. Energy model for blue brain environment

Energy conservation and energy balancing are important considerations while developing a Blue Brain network's routing system. The goal of this research is to develop a routing method that prolongs node lifespans while consuming less energy in networks. To minimize energy loss, we considered the networks variability on three different tiers, depending on the baseline energy of each Blue Brain node. All of the Blue Brain nodes in the network run static systems. It is true that the smallest energy initial stage nodes are called regular Blue Brain nodes, the intermediate energy second tier nodes are called intermediary Blue Brain nodes, and the highest energy third tier nodes are called expert Blue Brain nodes.

Let μ0 indicate the starting energy of regular Blue Brain nodes, μ0(1 + P) the beginning energy of expert Blue Brain nodes, and μ0(1 + P) the beginning energy of intermediary Blue Brain nodes. Equations 1-3 reflecting the total amount of energy of the regular, intermediary, and expert Blue Brain nodes.

$$\mu_{Re} = k\mu 0(1 - p - q) \tag{1}$$

$$\mu_{In} = kq\mu 0(1 + Q) \tag{2}$$

$$\mu_{ex} = kp\mu 0(1 + P) \tag{3}$$

The energies of the regular Blue Brain node are denoted by Re in this instance, those of intermediary Blue Brain nodes by In, and those of advanced nodes by An. The networks expert Blue Brain nodes are denoted by the symbol p, and their energy level is P. The networks intermediary Blue Brain is denoted by the letter p, and their energy level is denoted by the formula Q = P/2; k denotes the size of the nodes within every category. The entire amount of network energy used is provided as Equation 4.

$$\mu_{entire} = k\mu 0(1 - p - q) + kq\mu 0(1 + Q) + kp\mu 0(1 + P) = k\mu 0(1+pP+qQ) \tag{4}$$

Furthermore, take into account the SEP and LEACH methodology models for choosing the CH. Depending upon their chances of choosing the CH, every kind of Blue Brain nodes cutoff is determined. Let S1, S2 and S3 represent the sets of Blue Brain nodes from every kind that were not chosen to serve as the CH. The Blue Brain nodes that should have been chosen are listed here.

Determine the average probabilities of choosing the CHs every cycle using Equations 5-9, and the result is displayed as Equation 10.

$$P_{Re}=P/(1+pP+qQ) \tag{5}$$

$$T_{K(Re)}=\{ P_{Re}/(1-[P_{Re}*amod(1/ P_{Re})]), 0 \text{ otherwise, if } K(Re)\in S_1 \tag{6}$$

$$P_{In}=[P(1+Y)]/(1+pP+qQ) \tag{7}$$

$$T_{K(In)}=\{ P_{In}/(1-[P_{In}*amod(1/ P_{In})]), 0 \text{ otherwise, if } K(In)\in S_2 \tag{8}$$

$$P_{ex}=P(1+Q)/(1+pP+qQ) \tag{9}$$

$$T_{K(ex)}=\{ P_{ex}/(1-[P_{ex}*amod(1/ P_{ex})]), 0 \text{ otherwise, if } K(ex)\in S_3 \tag{10}$$

$$k(1-p-q)\, P_{Re} + kpP_{ex} + kqP_{In} = kP \tag{11}$$

The overall possibility of choosing CHs as determined by Equation 11, is identical to a value of a LEACH approach in a heterogeneous network.

The communication protocol for a heterogeneous Blue Brain network is shown in Figure 3. A multipath propagation or free space framework is used to calculate the energy transfer in the heterogeneous environment. The Blue Brain node requires energy to communicate 'n' bits per package, as can be seen from the communication mechanism illustrated in Equations 12 and 13.

$$\mu Tr(n, r) = \mu_{Tr\_ele}(n) + \mu_{Tr\_amp}(n, r)$$
$$\mu Tr(n, r) = \mu_{ele}\times n + \mu_{fs} \times n \times r^2, r \le r_0 \tag{12}$$

$$\mu_{ele}\times n + \mu_{mp} \times n \times r^4, r>r^0 \tag{13}$$

The terms " μ_{fs}" and "μ_{mp}" refer to the amplifiers settings for sending packets in free channels and multipath fading channels, respectively. The Blue Brain nodes energy consumption while transmitting the packet is indicated by the symbol μ_{ele}. The Equation 14 is a list of the required energy to obtain the package.

By measuring the amount of energy used during every cycle, the energy cutoff level for CH selection is calculated. To extend the lifespan of Blue Brain environment, the proposed methodology in Figure 3 calculates energy dissipation cutoff level for any and all kinds of Blue Brain nodes.

$$\mu Rc(n) = \mu Rc\_ele(n) + n\mu_{ele} \tag{14}$$

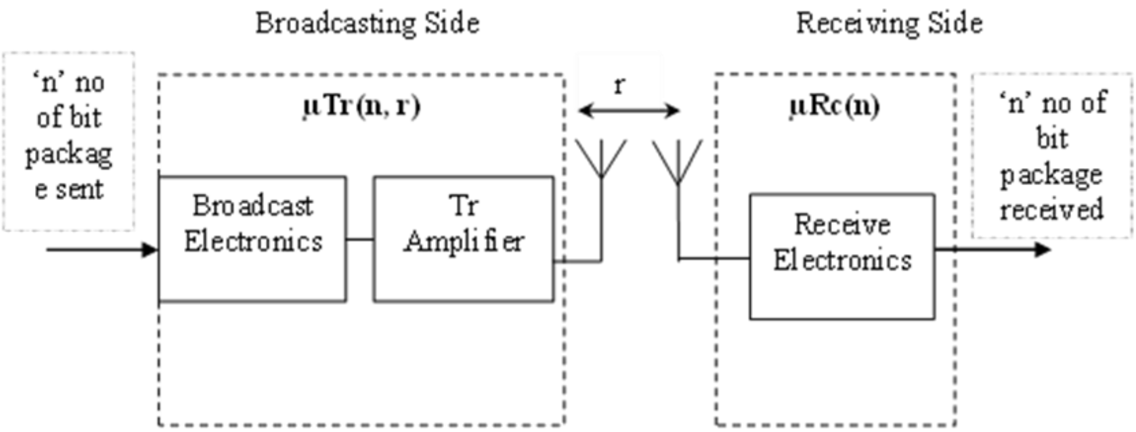

Figure 3. Communication representation for Blue Brain nodes.

3. Proposed Methodology (ECHSD)

The Blue Brain nodes use the ADV notification within the cluster to interact with the CH instantly, even before the CH is selected. Once every cycle, the CH and its Blue Brain nodes will switch places. Any type of Blue Brain node that is in close proximity to a sink node uses less energy when sending packets than other types of nodes. Throughout the ensuing rounds, the clusters that were closest to a sink Blue Brain node would retain their CHs and current member Blue Brain nodes. Within a Blue Brain network, the suggested methodology addresses the energy dissipation threshold level for all types of Blue Brain nodes. Based on this threshold level, each clusters CH and member Blue Brain nodes will move on to the next step. The amount of energy left in the CH is calculated at the end of each cycle. If the residual energy value is less than the cutoff point, the network initiates the construction of a new cluster and a new CH election process. The proposed method reduces the energy consumption of both the routing information advertisement and the creation of new CH. Energy requirements for the Blue Brain node and the CH will never be equal. Additional responsibilities for the CH include data collection, consolidation, and forwarding. Hence, compared to the other Blue Brain nodes, the CH will use more energy. Therefore, if the CH really does change into a standard Blue Brain node, the suggested methodology gives the CH a high amplifying energy and gives that particular Blue Brain node a lowered amplifying energy in the cycle that follows.

Let s denote the overall amount of Blue Brain nodes with in Blue Brain network and u the proportion of clusters inside it. The CH replenishment count is denoted by the letter S. The length of the package to be accepted is represented by μn_{Rc}, whereas the length of the package to be broadcast is represented by μn_{Tr}. In Equation 15 "µS" denotes the energy expended for the formation of new clusters and the replacing of cluster heads.

$$\mu S = \{\mu n_{Tr}\, \mu_{Tr} + \mu n_{Rc}\mu_{Rc}(cs - 1)\}CS \tag{15}$$

where CS= cs signifies the size of a cluster and μ_{Tr} the amount of energy used to send eight bits of information. The energy required to receive eight bits of information is represented by the symbol $\boldsymbol{\mu}_{Rc}$. Calculating the starting energy given to all three categories of nodes regular, intermediary, and expert within the cluster yields the cluster energy usage. **µ**Z denotes the cluster's energy consumption, which is represented as Equations 16-18.

$$\mu Z(Re) = \mu_0 \times cs \tag{16}$$

$$\mu Z(In) = \mu_0(1 - Q) \times cs \tag{17}$$

$$\mu Z(ex) = \mu_0(1 - P) \times cs \tag{18}$$

Depending just on node higher energy across both scenarios the Blue Brain node functioning as Blue Brain node and the CH functioning as CH the energy consumption of every cluster is calculated for a single cycle (Equation 19).

$$\mu C(\delta) = \{(Q\delta - 1)\, \mu nTr\mu Tr \times \mu nRc\mu Rc\} + \{(Q\delta - 1)\, \mu nTr\mu Tr + (Q\delta - 1)\, \mu nRc\mu Rc\} \tag{19}$$

The symbol eµTr represents the amount of energy used by the Blue Brain node to transport the packages to the CH. There at CH end, the energy used for data gathering is expressed as $e(Q\text{-}1)_{\mu Rc}$. Overall energy used by the CH to the forward data towards the sink Blue Brain node is expressed as $e(Q-1)_{\mu Tr}$. If no packets of data are being transmitted or received, the Blue Brain nodes enter a stable state.

The total number of repetitions must be taken into account when determining the energy cutoff value for replacing the CH. α compute the total cycles in the following manner for the regular, intermediary, and expert Blue Brain nodes (Equation 20-22):

$$\alpha(Re) = \mu C / \mu Z(Re) \times 100 \quad (20)$$

$$\alpha(In) = \mu C / \mu Z(In) \times 100 \quad (21)$$

$$\alpha(ex) = \mu C / \mu Z(ex) \times 100 \quad (22)$$

Equations 19-22 yield the projected energy cutoff value for CH selection, which would be expressed as (Equation 23-24):

$$\mu CO(Re) = \alpha(Re)(\mu n_{Tr} + \mu n_{Rc})\mu_{Tr} \quad (23)$$

$$\mu CO(In) = \alpha(In)(\mu n_{Tr} + \mu n_{Rc})\mu_{Tr} \quad (24)$$

$$\mu CO(ex) = \alpha(ex)(\mu n_{Tr} + \mu n_{Rc})\mu_{Tr} \quad (25)$$

The projected ranges for the expert, intermediary, and regular Blue Brain nodes are represented by μCO(ex), μCO(In), and μCO(Re). The CH is to be replaced with the suggested energy cutoff model, that maximizes Blue Brain node lifespan and lowers energy use. The energy cutoff model for ECHSD is depicted in Algorithm 1 that attempts to enhance system performance.

Algorithm 1

Input:
μCO indicates the energy threshold value for CH election,
$SD_{(n)}$indicates the set of non-CH Blue Brain nodes,
SD indicates the Blue Brain node.
μres represent CH remaining energy,
CHN indicates the CH number.
Begin
1. for u in 1 to max do
2. W = 0;
3. Calculate the possibilities for **Re**, In and **ex**by means of the Equations. (5), (7) and (9);
4. Calculate the threshold cost for **Re**, In and **ex**by means of the Equations. (6), (8) and (10);
5. W = W + 1;
6. if G = = W then
7. High augmentation energy is allocated to W;
8. else
9. Low augmentation energy is assigned to G;
10. end if
11. for **δ** in 1 to n do
12. Alter the remaining energy μres of the Blue Brain nodes by means of the Equations (13) and (14);
13. Calculate the energy cutoff value for **Re**, In and **ex** from Equations (23–25);
14. if (μres<**μCO**(**Re**)&&μres<**μCO**(In)&&μres <**μCO**(**ex**)) then
15. The fresh CH is nominated from SD
16. else
17. Continue the similar CH for further cycle;
18. end if
19. end for
20. end for end

4. Results

The ECHSD simulation is conducted using NS_2. The 200 m^2 area used for the simulation has 200 Blue Brain nodes evenly spaced out over it. The sink Blue Brain node and other Blue Brain nodes are mobile and have infinite energy. Table 1 lists the variables that are used in the simulation environment. The efficacy of the proposed ECHSD protocol is compared with existing protocols such as LEACH, AHP, and BCDSD. The values of x and X are subject to alter based on a variety of factors, while the value of Y remains constant at 0.3.

Table 1. Simulation parameters.

Factors	Value
Remoteness among Blue Brain nodes	85m
Energy utilized for data accumulation (μDA)	5nJ/bit
Energy utilized for free space model (μfs)	10 $pJ/bit/m^2$
Energy utilized for amplifier (μamp)	100 $pJ/bit/m^2$
Packet size	3000 bits
Energy utilized for receiving (Rc)	0.013 $pJ/bit/m^4$
Total energy of the network (μTr, μRc)	50 J

Utilizing transmission rate, the ECHSD routing protocols effectiveness is evaluated. By enhancing the packet delivery ratio, this refers to the quantity of packages that were effectively delivered. In the initial scenario, the x number is assumed to be 0.1 and the X value to be 1. In the second instance, x is assumed to be 0.2 and X to be 1. The system is divided into three categories: expert Blue Brain nodes (10%), intermediary Blue Brain nodes (30%), and regular Blue Brain nodes. The robustness of the system is depicted in Figure 4 and 5, in which the number of iterations rises till the sensors inevitably collapse. The expert Blue Brain nodes in Figure 4 are assumed to represent 10% of the entire network.

It is discovered that compared to certain other clustering techniques, LEACH has a noticeably shorter network lifespan. The LEACH protocol can be implemented successfully in a homogeneous network but not in a heterogeneous one. Improved results are obtained when comparing the new ECHSD protocol with SEP, Z-SEP, and LEACH approaches. In contrast to the

BCDCP, it shows a 26% increase in network longevity. In Figure 5, 20% of a broadcaster's means algorithm represents expert Blue Brain nodes. The ECHSD protocol increases the system lifetime by about 34%, especially when compared to BCDCP.

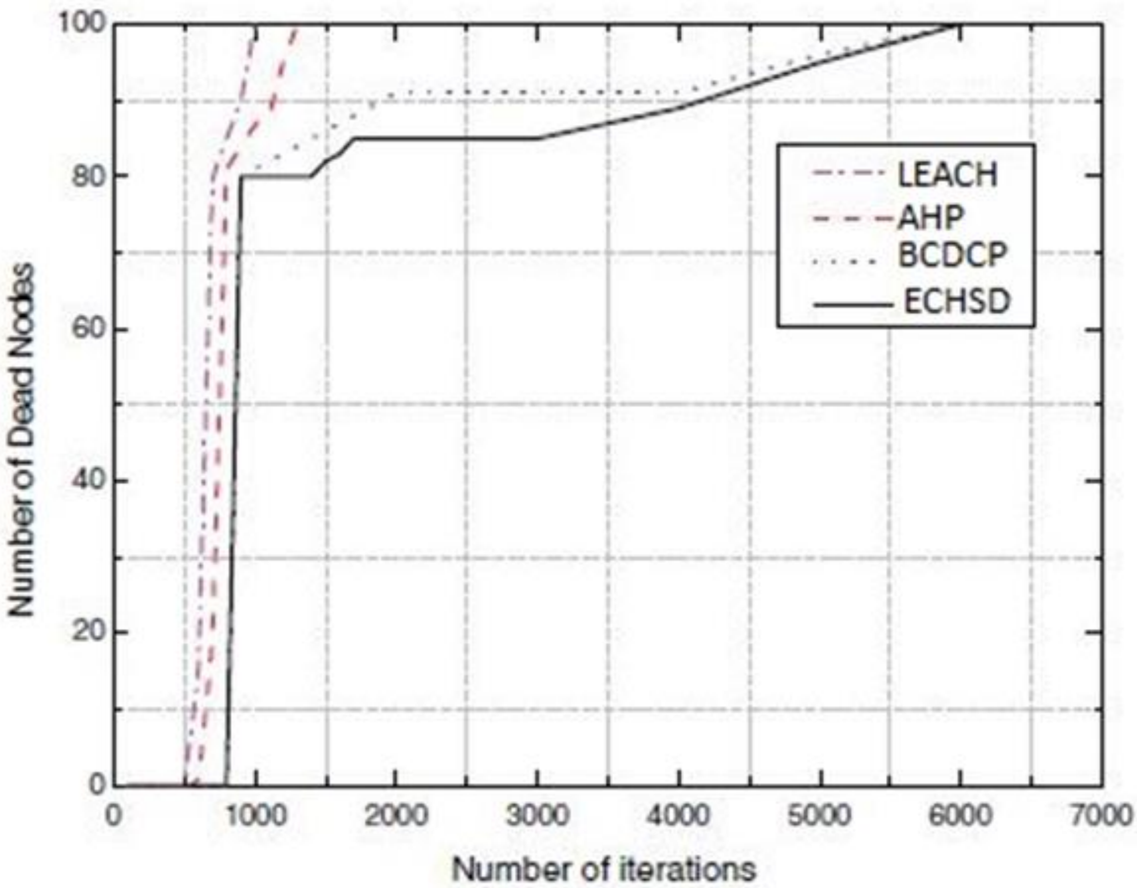

Figure 4. Network duration when x=0.1.

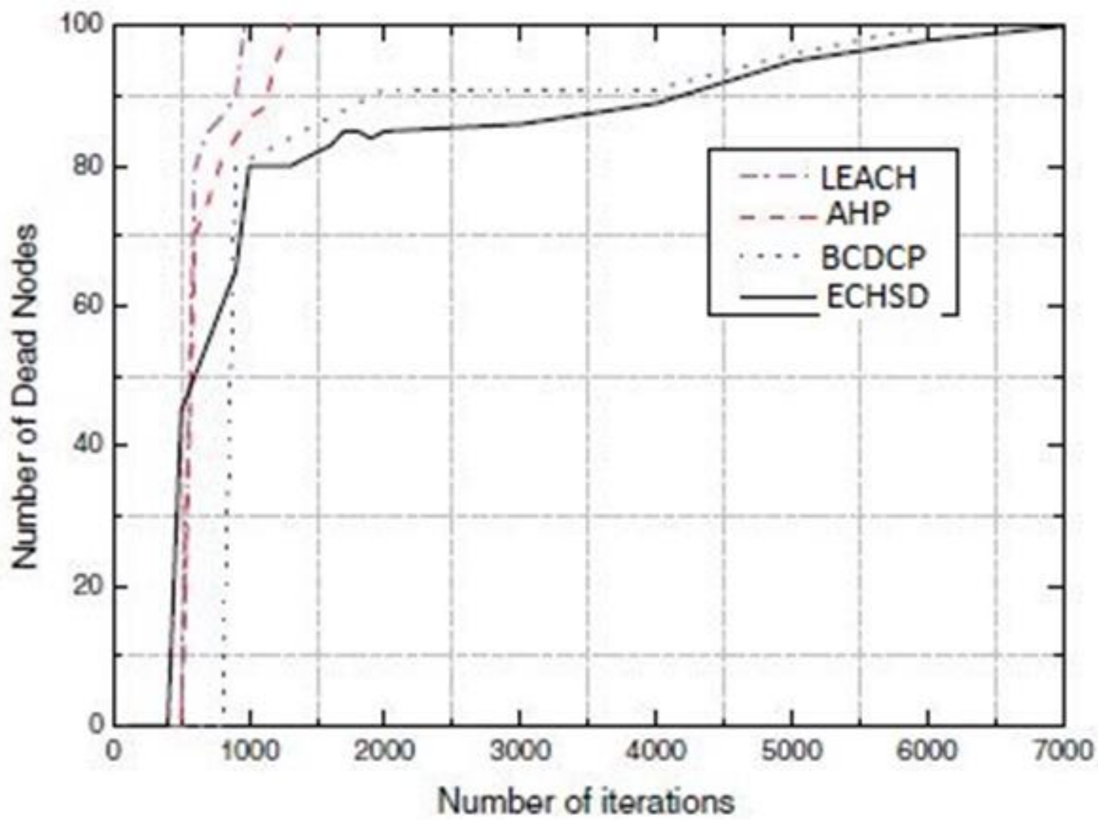

Figure 5. Network duration when x=0.2.

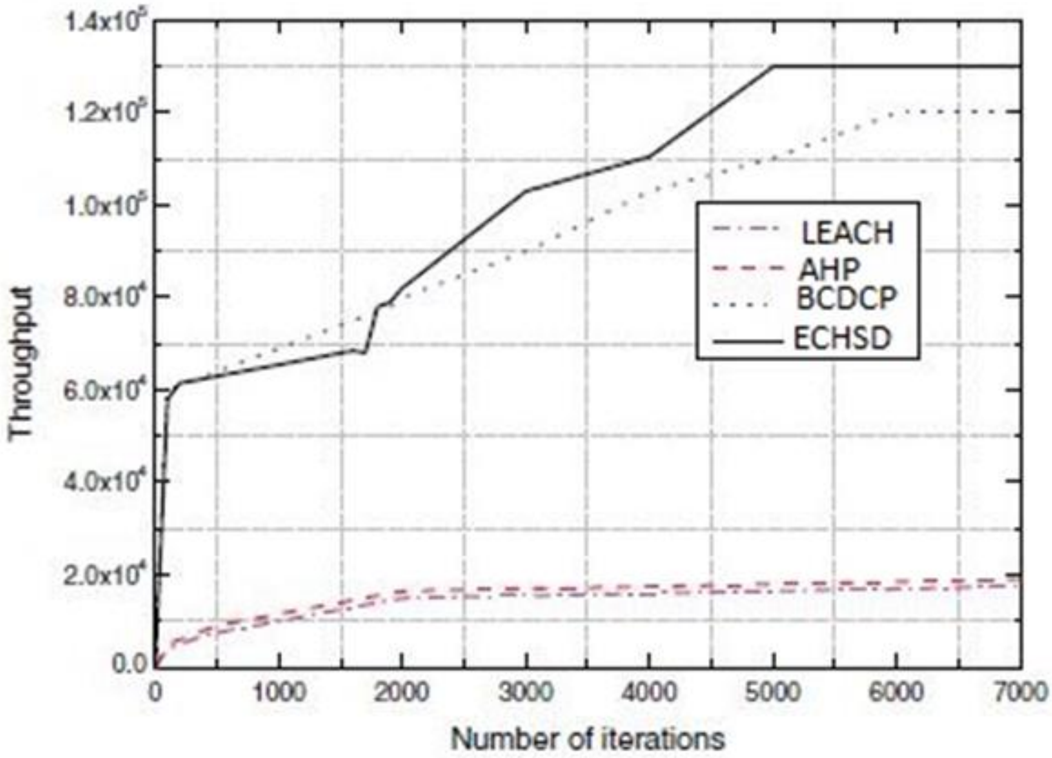

Figure 6. Network throughput when x=0.1.

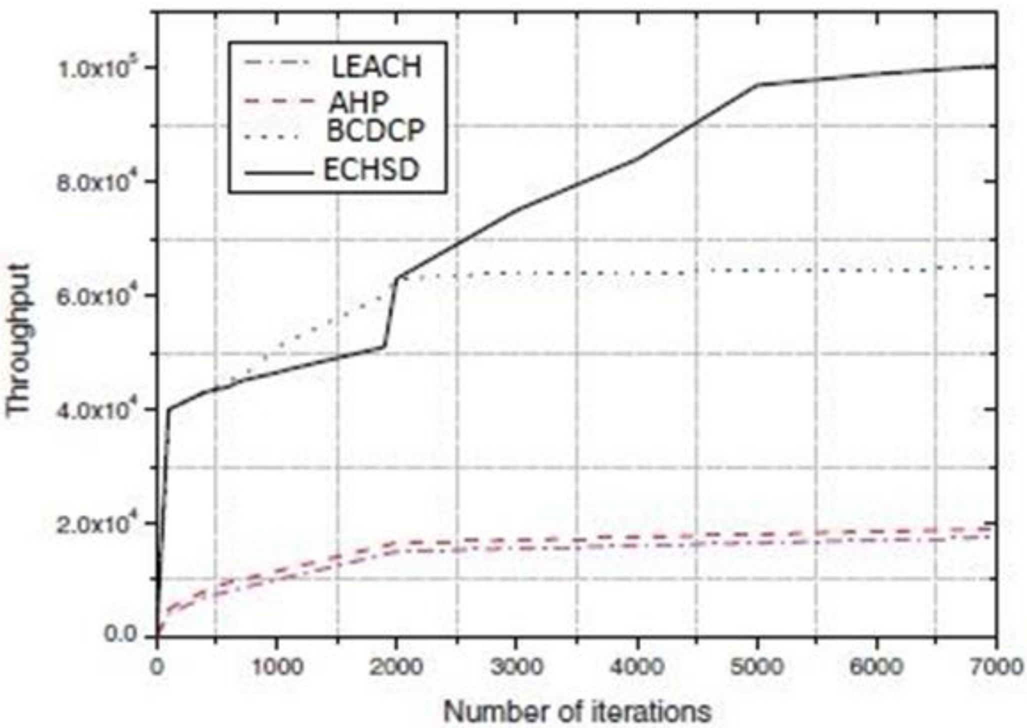

Figure 7. Network throughput when x=0.2.

Figure 6 and 7 show the network throughput that was achieved using the LEACH, AHP, BCDSD, and ECHSD approaches. In the first instance, the recommended routing protocol performed better than other algorithms when 10% of expert Blue Brain nodes were used. In terms of performance, it outperformed the AHP by 65% and the BCDCP by 28%. In the second scenario, where there are 20% more expert Blue Brain nodes, the system data transmission rate increases. ECHSD experiences a 39% improvement in throughput rate compared to BCDCP. Information gathering amongst Blue Brain nodes depends on CHs. The CHs collect data and forward it to the sink Blue Brain node. Figure 8 and 9 shows the evolution of CHs during each iteration. It has been demonstrated that fewer CHs maintain network power and increase data transmission capacity. With 10% fewer expert Blue Brain nodes than the LEACH and AHP instances in the first scenario, the ECHSD has less CHs. The ECHSD hits around 10–12 CHs every cycle. In the second instance of each cycle, the ECHSD attains roughly 6 to 8 CHs using 20% expert Blue Brain nodes.

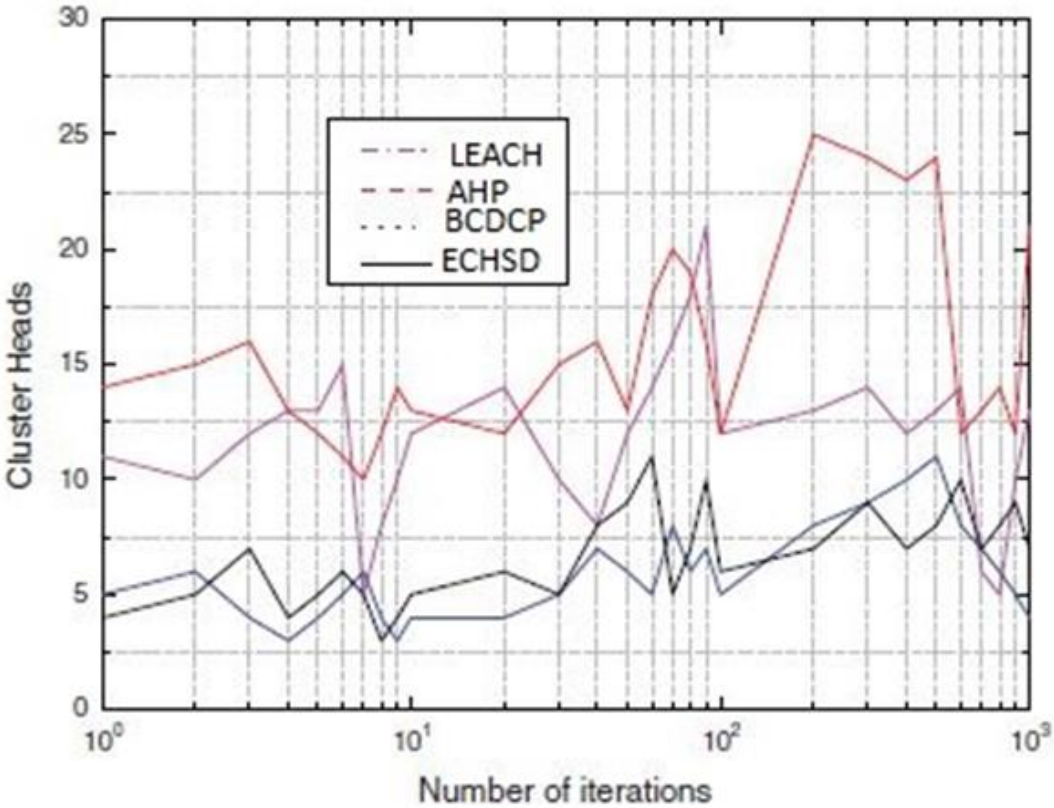

Figure 8. Cluster head amount in particular cycle when x = 0.1.

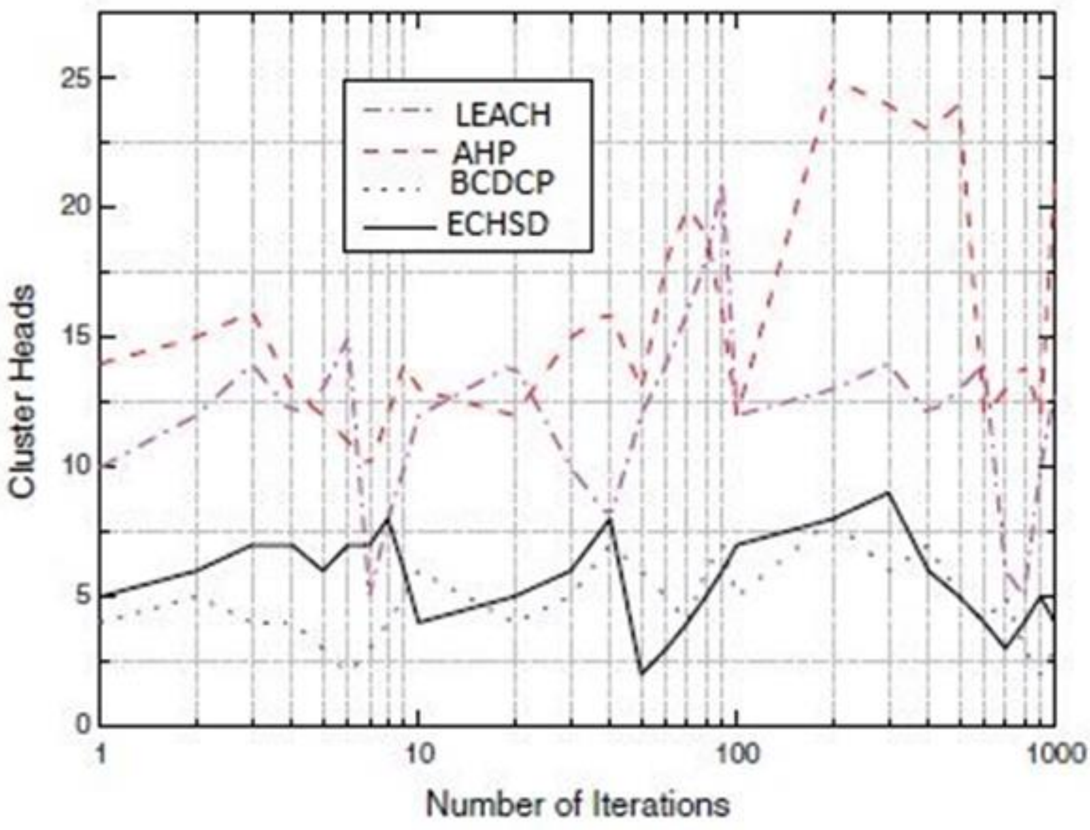

Figure 9. Cluster head amount in particular cycle when x = 0.2.

5. Conclusion

An energy-conscious strategy based on a cutoff parameter for a productive Blue Brain environment was used in this study. Current methods, such as the AHP and LEACH protocols, perform poorly in heterogeneous networks and perform best in homogeneous networks. Many energy-constrained Blue Brain nodes inside a real-time context comprise the Blue Brain environment. Even while some devices, such as smart watches and phones, can be recharged, certain Blue Brain nodes have limited power, therefore it's still important to lower their energy requirements. The suggested method divides Blue Brain nodes into three types using different energy cutoff stages. Different amounts of energy are consumed by Blue Brain nodes and CHs that are part of the system. This energy is distributed and managed using the recommended ECHSD protocol. The efficiency of the ECHSD approach is demonstrated by a simulation study in comparison to other existing protocols. Using Blue Brain in real time across large areas is one advantage of the ECHSD approach.

Author contributions

Rajesh Dennison: Conceived of the presented idea, Developed the theory, prepared original manuscript. **Giji Kiruba Dasebenezer:** Performed the computations and verified the analytical methods. **Ramesh Dennison:** Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

References

1. Rajesh, D., & Kiruba, D. G. (2021). A probability based energy competent cluster based secured ch selection routing EC2SR protocol for smart dust. Peer-to-Peer Networking and Applications, 14(4), 1976-1987. https://doi.org/10.1007/s12083-021-01144-z
2. Škulj, G., Sluga, A., Bračun, D., & Butala, P. (2019). Energy efficient communication based on self-organisation of IoT devices for material flow tracking. CIRP annals, 68(1), 495-498. https://doi.org/10.1016/j.cirp.2019.03.012
3. Huang, Y., Yu, W., Ding, E., & Garcia-Ortiz, A. (2019). EPKF: Energy efficient communication schemes based on Kalman filter for IoT. IEEE Internet of Things Journal, 6(4), 6201-6211. https://doi.org/10.1109/JIOT.2019.2900853
4. Kiruba, D. G., & Benitha, J. (2022). Fuzzy Based Energy Proficient Secure Clustered Routing (FEPSRC) for IOT-MWSN. Journal of Intelligent and Fuzzy Systems. 43(6),7633–7645. https://doi.org/10.3233/JIFS-212014
5. Alhakbani, N., Hassan, M. M., Ykhlef, M., & Fortino, G. (2019). An efficient event matching system for semantic smart data in the Internet of Things (IoT) environment. Future Generation Computer Systems, 95, 163-174. https://doi.org/10.1016/j.future.2018.12.064
6. Kiruba, D. G., & Benita, J. (2022). A survey of secured cluster head: SCH based routing scheme for IOT based mobile wireless sensor network. ECS Transactions, 107(1), 16725. https://doi.org/10.1149/10701.16725ecst
7. Vankadara, S., & Dasari, N. (2020). Energy-aware dynamic task offloading and collective task execution in mobile cloud computing. International Journal of Communication Systems, 33(13), e3914. https://doi.org/10.1002/dac.3914
8. Kiruba, G. (2022). A comparative study on energy efficient secured clustered approaches for IOT based MWSN. Suranaree Journal of Science & Technology, 29(4), 010151
9. Mitton, N., Costa, L. H. M., Krishnamachari, B., Pecorella, T., Tahiliani, M., & Puech, N. (2020). Green data collection and processing in smart cities. Annals of Telecommunications, 75, 269-270. https://doi.org/10.1007/s12243-020-00773-4
10. Kiruba, G. B. (2021). Energy capable clustering method for extend the duration of IoT based mobile wireless sensor network with remote nodes. Energy Harvesting and Systems, 8(1), 55-61. https://doi.org/10.1515/ehs-2021-0006
11. Rajab, A. D. (2022). Energy-Efficient Static Data Collector-based Scheme in Smart Cities. Computers, Materials & Continua, 72, 2077-2092. https://doi.org/10.32604/cmc.2022.025736
12. Al-Kaseem, B. R., Taha, Z. K., Abdulmajeed, S. W., & Al-Raweshidy, H. S. (2021). Optimized energy–efficient path planning strategy in WSN with multiple mobile sinks. IEEE Access, 9, 82833-82847. https://doi.org/10.1109/ACCESS.2021.3087086
13. Justus, J. J. & Thirunavukkarasan, M., Dhayalini, K., Visalaxi, G., Khelifi, A., Elhoseny, M. (2022). Type ii fuzzy logic based cluster head selection for wireless sensor network. Computers, Materials & Continua, 70(1), 801–816. https://doi.org/10.32604/cmc.2022.019122
14. Xie, Q., Li, K., Tan, X., Han, L., Tang, W., & Hu, B. (2021). A secure and privacy-preserving authentication protocol for wireless sensor networks in smart city. EURASIP Journal on Wireless Communications and Networking, 2021(1), 1-17. https://doi.org/10.1186/s13638-021-02000-7
15. Sivaram, M., Porkodi, V., Mohammed, A. S., & Karuppusamy, S. A. (2021). Improving Energy Efficiency in Internet of Things using Artificial Bee Colony Algorithm. Recent Patents on Engineering, 15(2), 161-168. https://doi.org/10.2174/18722121149992006161 6 4642
16. Gupta, P., Tripathi, S., & Singh, S. (2021). RDA-BWO: hybrid energy efficient data transfer and mobile sink location prediction in heterogeneous WSN. Wireless Networks, 27, 4421-4440. https://doi.org/10.1007/s11276-021-02678-z
17. Kamarei, M., Patooghy, A., Shahsavari, Z., & Salehi, M. J. (2020). Lifetime expansion in WSNs using mobile data collector: A learning automata approach. Journal of King Saud University-Computer and Information Sciences, 32(1), 65-72. https://doi.org/10.1016/j.jksuci.2018.03.006

18. Osamy, W., Khedr, A. M., El-Sawy, A. A., Salim, A., & Vijayan, D. (2021). IPDCA: intelligent proficient data collection approach for IoT-enabled wireless sensor networks in smart environments. Electronics, 10(9), 997. https://doi.org/10.3390/electronics10090997
19. Dande, B., Chen, S. Y., Keh, H. C., Yang, S. J., & Roy, D. S. (2021). Coverage-aware recharging scheduling using mobile charger in wireless sensor networks. IEEE Access, 9, 87318-87331. https://doi.org/10.1109/ACCESS.2021.3088524
20. Gharaei, N., Al-Otaibi, Y. D., Butt, S. A., Malebary, S. J., Rahim, S., & Sahar, G. (2020). Energy-efficient tour optimization of wireless mobile chargers for rechargeable sensor networks. IEEE Systems Journal, 15(1), 27-36. https://do.org/10.1109/JSYST.2020.2968968
21. Choi, H. H., & Lee, K. (2021). Cooperative wireless power transfer for lifetime maximization in wireless multihop networks. IEEE Transactions on Vehicular Technology, 70(4), 3984-3989. https://doi.org/10.1109/TVT.2021.3068345