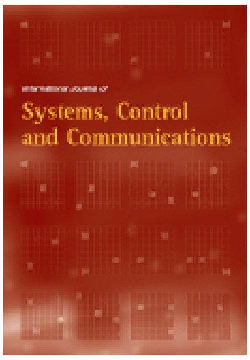


International Journal of Systems, Control and Communications

ISSN online: 1755-9359 - ISSN print: 1755-9340
https://www.inderscience.com/ijscc

Dynamic framework towards sustainable and energy-efficient routing in delay tolerant IoT-based WSNs

Sujit Bebortta, Sumanta Kumar Singh, Mamata Rath, Tanmay Mukherjee

DOI: 10.1504/IJSCC.2024.10060462

Article History:

Received:	02 February 2023
Last revised:	03 April 2023
Accepted:	18 April 2023
Published online:	01 December 2023

Dynamic framework towards sustainable and energy-efficient routing in delay tolerant IoT-based WSNs

Sujit Bebortta*

Department of Computer Science,
Ravenshaw University,
Cuttack, Odisha, 753003, India
Email: sujitbebortta1@gmail.com
*Corresponding author

Sumanta Kumar Singh

Department of Computer Science and Engineering,
Gandhi Institute for Education and Technology,
Odisha, 751001, India
Email: sksingh@giet.edu.in

Mamata Rath

Department of Computer Science and Engineering,
DRIEMS (Autonomous) College,
Cuttack 754025, Odisha, India
Email: mamata.rath200@gmail.com

Tanmay Mukherjee

Department of Computer Science and Engineering,
Siksha 'O' Anusandhan (Deemed to be) University,
Bhubaneswar, 751030, India
Email: utanmay10@gmail.com

Abstract: In wireless communication, energy efficiency is a crucial consideration. Wireless sensor networks (WSNs) are made up of a large number of sensor nodes scattered across a wide geographic area. When WSNs and the internet of things (IoT) come together, they create a complex network with interconnected devices of heterogeneous type. Energy restoration becomes crucial in order to prolong network lifespan and avoid sensor node (SN) failures. In order to overcome delays, a protocol that reduces energy loss while enhancing overall network performance is crucial. In this paper, we suggest the strategic cluster head selection (SCHS) model, a unique strategy for dealing with the task of choosing the best cluster head (CH) as a linear programming problem. Comparative simulations show that SCHS performs better than popular protocols like LEACH and PEGASIS in terms of average energy consumption, SN residual energy, sensing energy, and average network delay.

Keywords: internet of things; IoT; wireless sensor network; WSN; energy efficiency; delay tolerance; clustering.

Reference to this paper should be made as follows: Bebortta, S., Singh, S.K., Rath, M. and Mukherjee, T. (2024) 'Dynamic framework towards sustainable and energy-efficient routing in delay tolerant IoT-based WSNs', *Int. J. Systems, Control and Communications*, Vol. 15, No. 1, pp.79–94.

Biographical notes: Sujit Bebortta received his BSc degree in Computer Science from Utkal University, Bhubaneswar, India, in 2016, his Master's degree in Computer Science from the School of Information and Computer Sciences, Ravenshaw University, Cuttack, India, in 2018, and the MTech degree in Computer Science and Engineering from the College of Engineering and Technology, Bhubaneswar, India, in 2020. He is currently pursuing the PhD degree in Computer Science with the School of Information and Computer Sciences, Ravenshaw University. His current research interests include resource allocation in interconnected wireless networks, internet of things, Ad hoc networks and sensor networks, machine intelligence, and randomised algorithm design.

Sumanta Kumar Singh is currently working as an Assistant Professor with the Department of CSE, Gandhi Institute for Education and Technology, Odisha. He received his MTech degree in Computer Science and Engineering from College of Engineering and Technology, Bhubaneswar. His current areas of interest include data mining, big data analytics, networking, and internet of things.

Mamata Rath has completed PhD (Comp.Sc) from S.O.A. University, India in 2017. Currently she is working as an Associate Professor (Comp.Sc) in DRIEMS (Autonomous) Engineering College, Cuttack. She has good number of research publications in reputed journals and conferences. She is the editor of four research books of international repute. Her area of research includes mobile computing, networking and communication.

Tanmay Mukherjee received his BSc degree in Information Science and Telecommunication from Ravenshaw University, Odisha, India in 2013 and MSc degree in Computer Science from Ravenshaw University in 2015. He has done his MTech in Computer Science and Engineering from Utkal University, Odisha, India in 2017 and his PhD in Computer Science from Ravenshaw University, Odisha, India in 2022. He has served as a Business Analyst in the Cloud Engineering offering with Deloitte Consulting India. Currently, he is serving as an Assistant Professor in the Department of Computer Science and Engineering, Siksha 'O' Anusandhan (Deemed to be) University, Bhubaneswar. His research interests include wireless communication, systems modelling and simulation.

1 Introduction

Rapid innovations in micro-electro-mechanical systems (MEMS) and embedded systems have contributed for a plethora of sensors, including temperature, pressure, vibration, humidity, flow, and position, among others, that are used to collect data in a variety of applications, including health monitoring, smart city, smart industry, surveillance, and smart grid, among others (Haseeb et al., 2020). Self-configuration, in which each sensor node (SN) configures itself with its nearby nodes and builds a routing path to the target, is one of the fundamental benefits of wireless sensor networks (WSNs) (Haseeb et al., 2020; Shukla and Tripathi, 2020). Finally, the sensor's data is sent to the data centre so that it may be processed and analysed quickly, avoiding societal and economic harm. It also minimises the complexity of hardware and human resources.

The internet of things (IoT) has emerged as the most promising technology to facilitate connectivity across various smart devices, objects, and things via the internet (Gopika and Panjanathan, 2020). By 2020, more than 50 billion devices will be connected to the internet, according to a CISCO estimate (Kaya et al., 2020). Radio Frequency Identification (RFID) and WSN are two of the most common IoT data providers. RFID tags are utilised to identify different devices in most industry automation procedures. Sensor data including vibration, temperature, humidity, pressure, and pictures are also utilised to assess product quality and gadget durability (Haseeb et al., 2020).

The recent advancements in WSNs and IoT, have facilitated in managing industrial automations without the involvement of humans (Haseeb et al., 2020; Shukla and Tripathi, 2020; Gopika and Panjanathan, 2020). This entails several advantages, including:

1 enhanced productivity and product quality

2 reduced routine checks

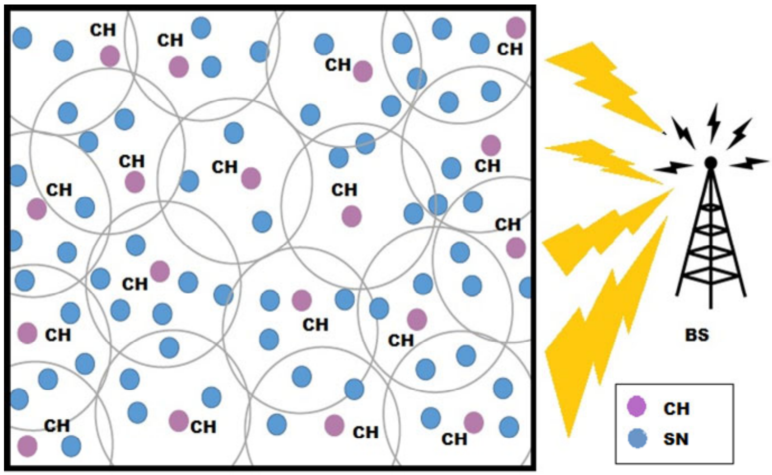
3 better safety standards

4 minimisation of number of personnel involved in automating a task, resulting in cheaper operating costs.

The nodes in WSNs must have enough battery power to support high data rates for accomplishing such mission critical tasks ((Haseeb et al., 2020). However, one of the major issues pertaining to WSNs is the constrained availability of node battery power, reducing the overall lifetime of the WSN. One of the most essential goals in WSNs is to reduce energy usage because SNs are installed in regions where battery replacement is difficult. SNs utilise energy to respond to query requests and to transmit and receive data (Gopika and Panjanathan, 2020). There could be several clusters in WSNs. The SNs associated with a cluster deliver their captured data to the cluster heads (CHs) assigned to them. From round to round, the CHs may alter. The sensory data is acquired by a CH and is transmitted to the base station (BS). There may be functionality for single or multi-hop for transferring data to the CH from different SNs. The SNs in single hop consume comparatively higher battery power since their distance from CH increases, but SNs in multihop consume lower battery power since their distance from CH decreases (Heinzelman et al., 2000).

This paper proposes the strategic cluster head selection (SCHS) model as a method for selecting optimal CH in WSNs. The SCHS model primarily considers objective function for minimising energy consumption (EC) and delay subject to two primary goal functions, i.e., energy level and distance of the nearest nodes. For this purpose, the constrained linear programming approach is used in our study. The model considers variables like the residual energy of SNs as well as communication path features like average intra-cluster distance among the SNs and the distance of SNs from the sink for an optimal CH selection with energy efficiency. The performance of the SCHS model is studied with well-known clustering models such as LEACH and Pegasis, through simulation experiments. In Figure 1, an overview of the IoT-based WSN setting for communication between CHs and BS is provided.

Figure 1 IoT-based WSN setup for communication between CHs and BS (see online version for colours)



2 Literature review

In Banđur et al. (2019), the use of WSN for smart agriculture applications was investigated. The paper's major objective was on reduction of power consumption for varying WSN components over physical and functional levels. The analysis contained comparison of conventionally used protocols over the physical layer, data, and network layers, as well as a discussion of their energy efficiency. The results of the research provided efficient identification of major power consuming SNs, the quantity of their consumption, and a thorough understanding of the essential modalities that must used to increase energy efficiency of WSNs.

In terms of multi hop – single hop communication and multi hop – multi hop communication, a sophisticated apprehension of chain routing protocols in WSNs that are successors to PEGASIS was presented in Khedr et al. (2021). The work presented an overview of the issues in building routing protocols for WSNs, followed by a qualitative survey focused on chain routing protocols along with details, benefits, and main drawbacks corresponding to each technique. Further, the features of the chain routing was presented along with the metrics that are used to evaluate performance.

The work proposed in literature Chithaluru et al. (2020), conceptualised the IoT framework to build a green-WSN that would improve sensor-based communication in future smart cities. Taking into account the criticality of appropriate steps for avoiding energy exhaustion in WSNs, this study offered an improved-adaptive ranking based energy-efficient opportunistic routing (I-AREOR) protocol which considers regional density, distance, and residual energy to balance EC and to maximise the network lifetime. Here, it was observed experimentally that the first node death, half node death, and ultimate node death were the main barriers to increasing energy efficiency. As a result, the suggested approach had considered regional density, relative distance of SNs, and the residual energy of the SNs to provide an explicit solution for extending the period of first node death.

Due to the open and resource constrained nature of IoT with WSN support, energy efficiency, and security, all of which are crucial for quality of service (QoS), remains a challenge till date. Keeping in mind the lack of high-level security mechanism for energy efficient WSNs, the work in Sujanthi and Kalyani (2020) proposed secure deep learning technique referred to as SecDL. This research dominated the problem of energy efficient security mechanism for WSN-IoT networks with dynamic clusters. To increase energy efficiency, the network was built as bi-centric hexagons using mobile sink technology. The dynamic clusters were established, and the best CHs were chosen using the quality prediction phenomenon to assure QoS and energy efficiency.

In the research Kang and Choo (2018), a global positioning system (GPS)-based energy-efficient routing technique was presented. Their proposed approach used beacon messages from the primary route nodes to track the location of the destination SNs. In comparison to current routing techniques like ladder diffusion and the energy-efficient ant-based routing algorithm (EEABR), the suggested approach was observed to increase the data packet delivery rate and reduce the overheads associated with routing control messages in the IoT network.

The paper in Preeth et al. (2018), presented energy-efficient clustering based on adaptive fuzzy rules and immune-inspired routing that was referred to as (FEEC-IIR) protocol for WSN aided IoT system to mitigate the concerns of low battery life and energy efficient selection of CHs. For the optimal CH selection, an energy-efficient clustering technique employing the AF-MCDM, an approach towards the adaptive fuzzy multi-criteria decision making that combines the fuzzy AHP (Wu et al., 2007; Huang et al., 2020) and TOPSIS (Hamzeloei and Dermany, 2016) methods, was developed. The primary elements that may influence the selection of CHs include metrics like energy parameter, QoS impact, and node placement, where each of these criterion contained a number of sub-criteria. Hence, to improve data transmission dependability, an immune-inspired optimisation technique was applied for routing. It was observed from the research that cluster-based routing was a cost-effective way to reduce EC in IoT. When compared to existing clustering and routing approaches, the experimental results showed that the FEEC-IIR model enhanced QoS metrics such as throughput, IoT network durability, end-to-end delay, and channel load, as well as other considerations like packet loss ratio, packet delivery ratio, buffer occupancy, bit error rate (BER), jitter, and EC.

Rechargeable WSNs provide effective data services for a variety of IoT applications since the sensors may be recharged continually (Guo et al., 2021). According to dynamic recharging planning, improving energy economy in networks with excellent QoS is essential. As a result, the paper Guo et al. (2021) offered a lifespan-balanced routing that is energy-efficient. In this case, the optimisation problem of optimising the recharging payout was addressed using the heuristic technique, which enabled dynamic modification for the ratio of moving time to recharging time based on node energy levels. Then, QoS routing was built using a multi-hop method that takes into account different related parameters. A lifespan indicator for energy was developed. In order to intelligently maximise the minimal lifespan of all nodes, the lifetime balancing strategy based on global relay range management was developed in conjunction with QoS routing.

The power limitations of WSN have become a challenge in the IoT network. One among a number of factors influencing power consumption in an SN is the routing protocol. The work in Ramadhan and Munadi (2021), extended the mechanism of PEGASIS framework to provide maximum life-time of WSN in IoT-enabled systems. Here, instead of passing the packets directly to the sink node, it facilitated CHs to form chain connections. The packets would be transferred from one CH to the next until it reaches the leader node (LN). Furthermore, the LN closest to the sink node in terms of distance was chosen. The proposed technique was based on comparisons with simulation findings from LEACH and PEGASIS.

3 Proposed framework

This section will provide the EC models for studying performance of IoT-based WSN. These models are further utilised to derive performance parameters for proposed SCHS model with other models. The study developed strategy for providing energy-efficiency and sustainability in SNs and eliminating delays for transmission of data frames in IoT network (Natesan and Krishnan, 2020; Ghosh et al., 2020; Biswas et al., 2020; Dhumane et al., 2020). The comparison is provided with two well-known protocols such as LEACH and Pegasis (Heinzelman et al., 2000; Khedr et al., 2021). The LEACH, signifies a WSN routing protocol with an emphasis on SN power usage. However, because the LEACH protocol's CH passes packets straight to the sink node, CHs that are further away from the sink node will exhaust its energy more quickly than a nearby one (Heinzelman et al., 2000; Iwendi et al., 2021; Wang et al., 2018; Thomas et al., 2021; Jerbi et al., 2019). The Pegasis protocol uses chaining mechanism to associate SNs and for CH selection, which further leads to long links, delays, and complexity in topological arrangement of SNs (Khedr et al., 2021; Gupta and De, 2021; Hester et al., 2017; Bourmada and Bilami, 2017; Kumar and Mathur, 2017; Singh and Rishiwal, 2020; Slimani et al., 2020). In comparison to the above discussed techniques, the proposed SCHS method has a longer lifetime, lesser delay, and provides suitability for heterogeneous IoT networks with more number of deployed SNs (Hester et al., 2017; Slimani et al., 2020).

3.1 Energy consumption (EC) model

It is critical to model an autonomous IoT network's energy usage for various jobs before designing it. Each task uses a certain amount of power for a set amount of time. In order to optimise the energy usage by the SNs in the IoT network and facilitate long communication range, it is considered in consistence with the low power wide area network (LP-WAN) communication protocol specifically allowing long range communication at lower bit rates.

The EC model for CH selection in WSNs is presented in this section. The following is a list of the energy consumed by various activities:

- EC for sensing: The energy usage as a result of the deployed sensors sensing in the IoT environment is significant to estimate in order to maintain the efficacy of overall IoT network. One of the most significant qualities of sensors is their ability to sense a system, which connects SNs to the actual environment. For some SNs deployed in an IoT setting such that $x_i \in X$ (say) and $i = \{1, 2, 3, \ldots, n\}$, then the amount of energy used by a SN to sense something may be denoted as $E_{sence}(x_i)$. Hence, we obtained the formulation to EC for sensing x_i sensors as provided below:

$$E_{sense}(x_i) = \tau_s * N_{packet} * v * t(x) \tag{1}$$

where τ_s represent the amount of current to sense the N_{packet} being transmitted by SNs x_i in the IoT network, v denoted the supplied voltage, and $t(x)$ gives time duration for the sensing session.

- Transmission energy: The energy consumed for transmitting N_{packet} transmission frames by x_i SNs in the IoT network is given as follows:

$$E_{Tx}(x_i) = \begin{cases} e_{txrx} * N_{packet} + \tau_{amp} * N_{packet} * \delta, & \delta \le \delta_0 \\ e_{txrx} * N_{packet} + \tau_{fs} * N_{packet} * \delta, & \delta > \delta_0 \end{cases} \tag{2}$$

where e_{txrx} provides EC for single SN in IoT network for transmitting and receiving the N_{packet} transmission data frame over a network, τ_{amp} denoted amplification factor used for tuning network performance, τ_{fs} is the amplification factor for free space model in IoT network, δ provided distance for any pair of SNs in the network, and finally δ_0 gives the average threshold distance.

- Energy for receiving the data frames: The total energy consumed for receiving or capturing data frames in IoT network corresponding to N_{packet} transmission frames by x_i SNs is given by

$$E_{Rx}(x_i) = e_{txrx} * N_{packet} \tag{3}$$

Here, in equation (3) $E_{Rx}(x_i)$ provided formulation for total EC in IoT network for receiving the data frames by x_i nodes.

- Energy for transitioning states: In our considered IoT network, the transition takes place between two sensor states, i.e., an active sensor state and passive sensor state. Therefore, the energy consumed to switching between the two states for x_i SNs is given as below:

$$E_{pa}(x_i) = \sum_i \left(e_{pa}\right)_i \tag{4}$$

where e_{pa} denotes energy for transitioning between states for a single SN and has been expressed as sum of i^{th} nodes in the network.

- Total energy of the network: Having obtained the above formulations for computing the energy usage by the IoT network we could easily obtained the overall EC. Thus, using equations (1) through (4), we get the total EC as below:

$$E_{total}(x_i) = E_{sense}(x_i) + E_{Tx}(x_i) + E_{Rx}(x_i) + E_{pa}(x_i) \tag{5}$$

- Residual energy: For some x_i SNs, the residual energy can estimated by considering the difference of the initial energy level for x_i SNs and the total energy for x_i SNs obtained by adding the energy depleted while the SN was in each state. We obtain the mathematical formulation for residual energy of nodes as the function $E_r(x_i)$ given in equation (6) below

$$E_r(x_i) = E_{init}(x_i) - E_{total}(x_i) \tag{6}$$

3.2 Delay model

In a time-constrained IoT-based WSNs environment, delay is a crucial QoS parameter for data forwarding. Delivery of time-critical events to the sink or BS within a particular deadline is a crucial feature for achieving QoS in IoT environments for the success of certain delay-aware applications like remote healthcare applications, military surveillance, monitoring of industrial automation, disaster management, and so on. In IoT, the end-to-end delay for transmission of data frames from one communicating device to another is of utmost importance. Like other QoS characteristics such as energy of nodes, dependability amongst nodes, data correctness, and coverage, the estimation of delay for the network is regarded as a significant parameter in determining the efficacy of the routing model for CH selection.

Thus for our considered network, the average delay in the network is considered as ϕ_{avg} which is represented by the difference in the transmission time for x_i SNs in the physical layer (destination node) and the transmission time for SNs in the application layer (source node). Thus, equation (7) provides the formulation used for estimating the average transmission delay for the IoT network as follows:

$$\phi_{avg} = t_{phy\_dest}(x_i) - t_{app\_src}(x_i) \tag{7}$$

where gives the transmission time for destination nodes in the physical layer and provides the transmission time for source nodes in application layer.

3.3 Strategic CH selection (SCHS) model

In this section, proposed SCHS model for energy efficient CH selection is developed. The proposed SCHS model serves the fundamental goal for selecting an optimal number of CHs from a set of SNs based on energy-efficient standards to increase the network's lifespan. The model operates by considering criterion such as residual energy of the SNs, as well as different distance characteristics such as the distance from the sink and the SNs' average intra-cluster distance, are taken into account for energy efficiency and optimal CH selection.

Now, considering k_1 to be a function representing the CHs' sink distance and the average intra-cluster distance. Hence, for optimal CH selection, we must reduce the value k_1. For k_2 being a function that is the inverse of the total current energy of all the CHs, the objective function K_i can be minimised for achieving optimal value of CH selection as obtained in equation (8).

$$Min\ K_i = \mu * k_1 + (1-\mu) * k_2 \tag{8}$$

Subject to constraints:

$$d\left(x_i, C_j\right) \le d_{\max}, \forall x_i \in X, C_j \in C \tag{9}$$

$$d(C_j, B) \le T_{\max}, \forall C_j \in C \tag{10}$$

$$E_{C_j} > \pi_{C_j}, 1 \le j \le n \tag{11}$$

$$0 < \mu < 1, \tag{12}$$

$$0 < k_1, k_2 < 1 \tag{13}$$

From equation (9) it can be noted that the distance of the x_i nodes in the IoT network with the C_j CHs require to be less or equal to the maximum communication distance or range for a SN signified by d_{max} in order to satisfy the objective function in equation (8). Hence, d_{max} can be obtained by maximising the below expression which is given as follows:

$$d_{\max} = \left(\left(\sqrt{(a_x - b_x)^2 + (a_y - b_y)^2}\right), \left(\sqrt{(a_x - c_x)^2 + (a_y - c_y)^2}\right)\right) \tag{14}$$

where $a(x, y)$, $b(x, y)$, and $c(x, y)$ denote the SNs in the IoT network with x and y as coordinates. It is pertinent to note that d_{max} denotes the maximum range between two SNs to facilitate communication, after which communication ceases. Therefore, our goal is to set $d(x_i, C_j)$, such that it is always less or equal to d_{max} in order to ensure uninterrupted communication between SNs while providing efficient selection of CHs.

In the constraint provided in equation (10) the distance between C_j and transmitting BS B is provided which requires to be less or equal to the maximum transmission range T_{max}. The constraint in equation (11) indicates that the energy E_{Cj} for C_j CHs must be higher than average set threshold energy level π_{C_j} for C_j CHs.

Further, the constraints in equations (12) and (13) ensures balance between weights of residual energy and distance between nodes, where μ signifies the control parameter such that neither of the both have weights 0% or 100% as in equation (12), i.e., residual energy for a SN should not be over-utilised or under-utilised. Similarly for the distance function of the nodes, i.e., k_1 and k_2 should not be in complete proximity or too far-away from the sink as indicated in equation (13).

At this point, it is worthwhile to mention that the ratio between the control k_1 and k_2 given as k_{12} should be optimised in order to provide a better choice of CH selection for the proposed SCHS model. Therefore, we normalise the above objective function in equation (8) as below:

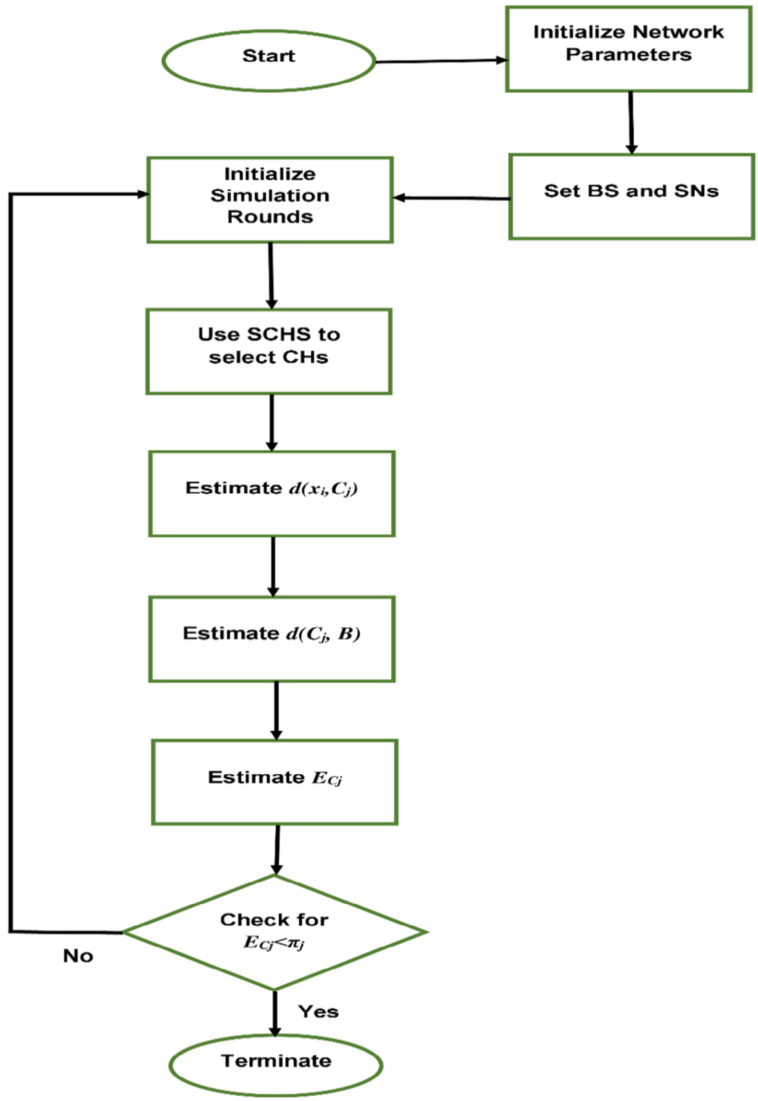
$$K_i = \frac{k - \min(k_1)}{\max(k_{1:2}) - \min(k_2)} \tag{15}$$

Thus, equation (15) normalised the two control variables k_1 and k_2 in such a manner between [0, 1] that it manages to efficiently reduce their linear combination.

From Figure 2 the control flow diagram for the proposed SCHS model can be observed. It is clear from the figure that initially the network parameters are setup like the simulation area, number of SNs to be deployed, location of BS, initial energy of nodes, number of transmission frames, and other important network parameters mentioned in the later section. The energy-efficient selection of CHs is done by employing SCHS model, subject to the objective function K_i. The distance corresponding to $d(x_i, C_j)$ and d(C_j, B) is achieved for the given network.

Finally, E_{C_j} is compared with the threshold energy level π_{C_j} for j^{th} clusters in the network setting. The energy of C_j CHs is compared for estimating their residual energy level. If $E_{C_j} < \pi_{C_j}$, the CH is observed to possess lower residual energy and is about to die, therefore the present CH is terminated. If $E_{C_j} > \pi_{C_j}$, then the CH possess residual energy above the average set threshold and hence can participate in the network.

Figure 2 Control flow for the proposed SCHS model (see online version for colours)



4 Experimental results

The experimentations have been conducted in a simulated IoT-based WSN environment with 500 SNs deployed across a desired sensing area of 400 × 400m2. using NS2 simulator. The LP-WAN framework has been used to establish the interconnection between the nodes which operates at a frequency of 868 MHz. The initial energy for each node was fixed at 3.6 mJ. The EC for transmitting and receiving was specified to 0.012 mJ and 0.321 mJ respectively. The specific value corresponding to the simulation parameters used for setting up the IoT network is provided in Table 1 which is consistent with the EC model presented in Section 3.1. Pertaining to those parameters we compare and contrast the performance of the proposed SCHS model with two other popularly used baseline models viz., LEACH (Heinzelman et al., 2000) and Pegasis (Khedr et al., 2021).

Table 1 Simulation parameter specification

Parameters	*Values*
Network area	400 × 400 m2
BS location	50 × 550 m2
Number of SN	500
$E_{init}(x_i)$	3.6 mJ
e_{txrx}	[0.012 mJ, 0.321 mJ]
N_{packet}	1,500 bits/s
τ_{amp}	1e-9mJ/bit/m2
τ_{fs}	2e-9mJ/bit/m2
d_{max}	≤ 5 m
π_{C_j}	1.5 mJ
δ_0	1.5 m
v	0.0045 V

5 Performance evaluation

Although the LEACH and Pegasis are one of the most popularly used hierarchical routing algorithms till date, they suffer some issues as the network size increases and the failure of SNs occurs. This encounters major challenges for implementation in IoT-based environments as they require fault-tolerance and reliable communication. Apart from this, these routing algorithms also face some limitations like delay overheads while transmitting and receiving of data frames, and varying network topology (Khedr et al., 2021). Further, the CH selection policy of LEACH is based on the threshold function rather than residual energy approach which further leads to deterioration of performance. Thus, in context to above challenges the proposed SCHS model is observed to improve performance in terms of energy efficiency and average delay in transmitting and receiving the packets in a heterogeneous IoT network. Further, intra-cluster distance and distance between sink nodes was considered in proposed SCHS model for obtaining energy-efficient selection of CHs. Thus, we provide comparison of our proposed SCHS model with LEACH and Pegasis models since it overcomes most of the shortcomings of these models. The results provided in Figures 3 through 6 provide performance of SCHS model with LEACH and Pegasis models for different performance metrics like average EC, energy consumed by each model for sensing, residual energy after implementing the models, and the average delay for models considered in this study.

Figure 3 Average energy consumption for different number of SNs deployed (see online version for colours)

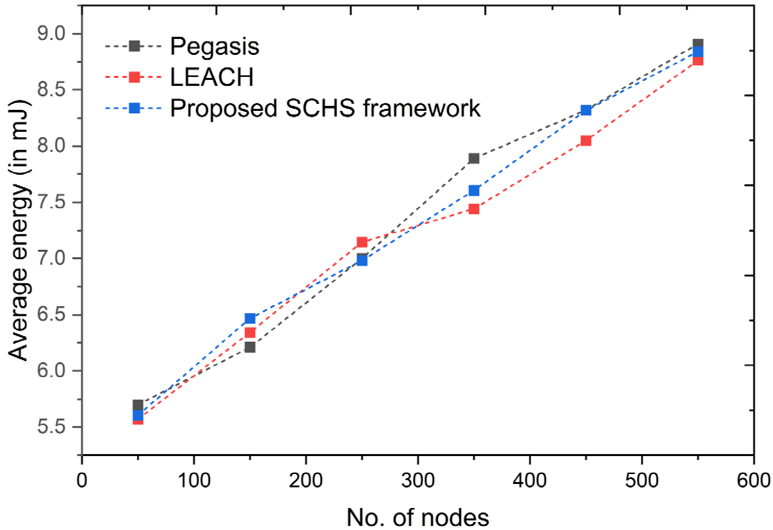
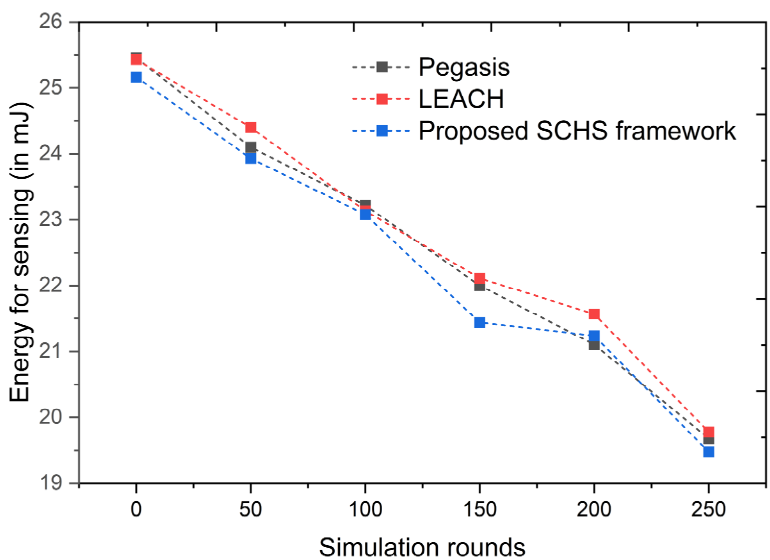


Figure 4 Energy consumed for sensing along with simulation rounds (see online version for colours)



The comparison of SCHS model to the baseline routing algorithms, i.e., LEACH and Pegasis is shown in Figure 3. In comparison to the previous techniques, the SCHS performs better, as seen in Figure 3 for the average energy consumed by the IoT network considered over different number of SNs. The number of SNs is represented on the X-axis, while the average energy consumed taken in mJ units is represented in Y-axis of Figure 3. It is obvious from Figure 3 that SCHS model has a relatively lower EC and therefore would have longer network lifetime than baseline methods.

Figure 5 The residual energy with number of simulation rounds (see online version for colours)

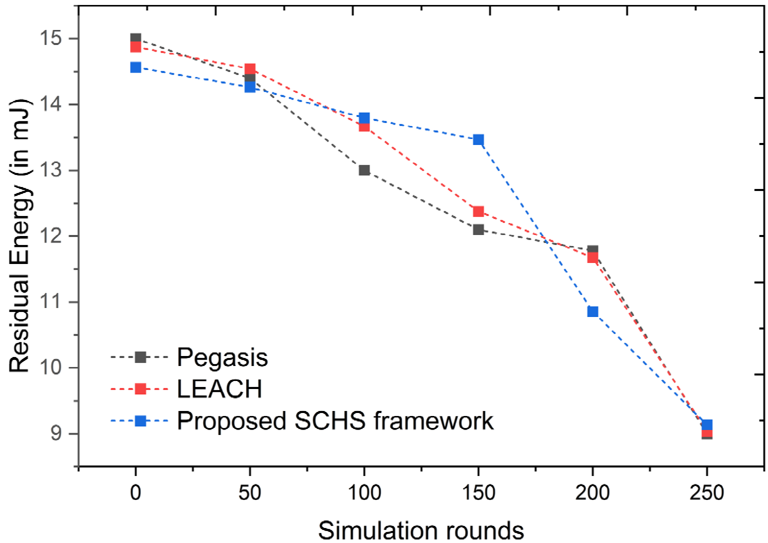
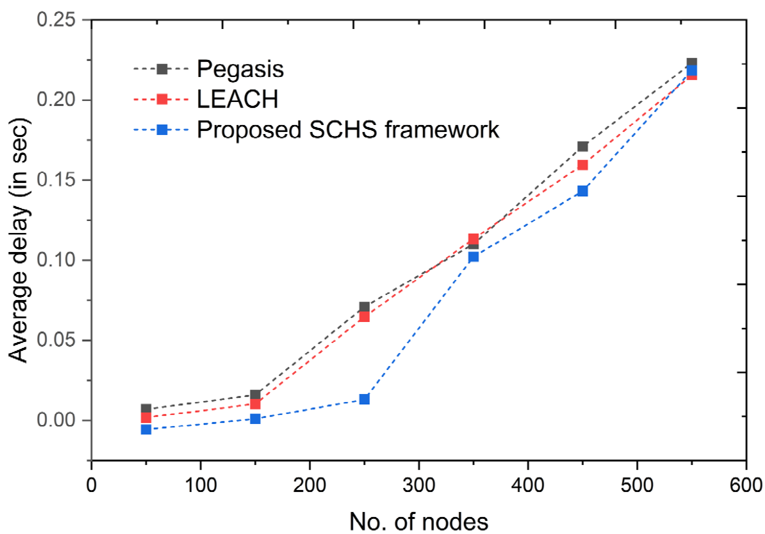


Figure 6 Average delay of the IoT network with number of SNs (see online version for colours)



The EC for sensing by each node in the simulated IoT network taken in mJ was provided in Figure 4 and was considered for 250 simulation rounds. It was observed at the end of the simulation number 250 that the energy consumed for sensing by the SCHS model for a node was $E_{sense}(x_i)$ = 19.01 mJ, but $E_{sense}(x_i)$ for LEACH and Pegasis was 19.78 mJ and 19.67 mJ respectively.

Figure 5 gives the plot for residual energy of the IoT network taken in mJ for different simulation rounds varying between 0 to 250. In comparison to the baseline models, the residual energy of the deployed nodes in SCHS is higher. Figure 5 shows that after 250 simulation rounds, the average residual energy for proposed SCHS model is

$E_r(x_i) = 13.0$ mJ, while residual energy for LEACH was $E_r(x_i) = 10.0$ mJ and for Pegasis was $E_r(x_i) = 9.0$ mJ.

The average delay for the IoT network taken in seconds was compared with respect to the number of deployed SNs in the simulation setup as provided in Figure 6. It is observed from the plot that the proposed SCHS model has lower average delay as compared with baseline LEACH and Pegasis models.

6 Optimality analysis of SCHS model

The selection of input parameters under constrained conditions and their normalisation procedure in SCHS model ensures uniform EC and extend network life till the battery runs out. The proposed SCHS model's optimality is attained on the following basis:

1. Using the distance function and the optimum number of CHs, i.e., C_j, the normalised value of the maximum distance between SNs and CHs is computed as shown in equation (9), which aids in assuring consistent EC of the SNs, and improving network energy efficiency.
2. The normalised value of average distance between CHs and the BS taken as $d(C_j, B)$ is calculated as equation (10) by taking into account the SNs' maximum transmission range T_{max}, which ensures the centre position with its member nodes, improves RSS quality, and saves a significant amount of battery energy by reducing data transmission over a long distance. It can observed in the Figure 4, that the energy consumed for sensing for SCHS model is relatively better in comparison with other two models. Also it is observed from Figure 6 that the average delay is extensively reduced for the proposed SCHS model as a result of optimal distance between BSs responsible for transmitting the received data frames.
3. The normalised value of residual energy is calculated using the greatest residual energy of the neighbour node instead of the SN's beginning energy, as shown in equation (11). It makes good use of the average energy threshold value π_{C_j}. If we utilise the SN's beginning energy to normalise the residual energy, the value of normalised residual energy drops over time, lowering the likelihood of becoming a CH and increasing the delay. The optimality of SCHS model in terms of residual energy can be seen in Figure 5, which is compared with LEACH and Pegasis.

Because an effective normalisation approach is used for selecting the goal functions k_1 and k_2 (in equation (14)), the suggested SCHS method provides a more stable network lifetime than LEACH and Pegasis.

7 Conclusions and future scope

This work provided an energy-efficient CH selection using the constrained linear programming approach for optimal CH selection. The metric for intra-cluster communication of the proposed SCHS model's energy efficiency, distance between nodes, residual energy, and average delay was provided alongside LEACH and Pegasis clustering techniques. The EC models were provided which facilitated computation of different performance metrics for the proposed SCHS model. The expression to obtain the average delay in the IoT network was given. The simulation experiments were provided to justify the efficiency of proposed SCHS model with LEACH and Pegasis. The model was tested with a variety of circumstances encountered in IoT-based WSNs. The suggested SCHS model outperforms existing algorithms in terms of overall EC, energy utilised for sensing, residual energy and the average delay in the network for transmission of data frames received by the BS, according to the experimental results

In the future, we would plan to use a meta-heuristic scheme to construct a routing algorithm for improving performance of the present model. We will explore several concerns such as energy balancing and WSN fault tolerance when developing such a model. We also plan to build the robust simulation technique for heterogeneous WSNs with would be in close approximation with realistic IoT networks.

References

Banđur, Đ., Jakšić, B., Banđur, M. and Jović, S. (2019) 'An analysis of energy efficiency in wireless sensor networks (WSNs) applied in smart agriculture', *Computers and Electronics in Agriculture*, January, Vol. 1, No. 156, pp.500–507.

Biswas, R.N., Mitra, S.K. and Naskar, M.K. (2020) 'Energy efficient and secure localization in wireless sensor networks: an approach through anchor mobility control', in *Novel Advancements in Electrical Power Planning and Performance*, pp.250–282, IGI Global, USA.

Bourmada, A. and Bilami, A. (2017) 'Cross-layer energy efficient protocol for QoS provisioning in wireless sensor network', *International Journal of Systems, Control and Communications*, Vol. 8, No. 3, pp.230–249.

Chithaluru, P., Al-Turjman, F., Kumar, M. and Stephan, T. (2020) 'I-AREOR: an energy-balanced clustering protocol for implementing green IoT in smart cities', *Sustainable Cities and Society*, October, Vol. 1, No. 61, p.102254.

Dhumane, A.V., Prasad, R.S. and Prasad, J.R. (2020) 'An optimal routing algorithm for internet of things enabling technologies', in *Securing the Internet of Things: Concepts, Methodologies, Tools, and Applications*, pp.522–538, IGI Global, USA.

Ghosh, A., Ho, C.C. and Bestak, R. (2020) 'Secured energy-efficient routing in wireless sensor networks using machine learning algorithm: fundamentals and applications', in *Deep Learning Strategies for Security Enhancement in Wireless Sensor Networks*, pp.23–41, IGI Global, USA.

Gopika, D. and Panjanathan, R. (2020) 'Energy efficient routing protocols for WSN based IoT applications: a review', *Materials Today: Proceedings*.

Guo, H., Wu, R., Qi, B. and Liu, Z. (2021) 'Lifespan-balance-based energy-efficient routing for rechargeable wireless sensor networks', *IEEE Sensors Journal*, Vol. 21, No. 24, pp.28131–28142.

Gupta, V. and De, S. (2021) 'Energy-efficient edge computing framework for decentralized sensing in WSN-assisted IoT', *IEEE Transactions on Wireless Communications*, Vol. 20, No. 8, pp.4811–4827.

Hamzeloei, F. and Dermany, M.K. (2016) 'A TOPSIS based cluster head selection for wireless sensor network', *Procedia Computer Science*, January, Vol. 1, No. 98, pp.8–15.

Haseeb, K., Ud Din, I., Almogren, A. and Islam, N. (2020) 'An energy efficient and secure IoT-based WSN framework: An application to smart agriculture', *Sensors*, Vol. 20, No. 7, p.2081.

Heinzelman, W.R., Chandrakasan, A. and Balakrishnan, H. (2000) 'Energy-efficient communication protocol for wireless microsensor networks', in *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences*, January, p.10, IEEE.

Hester, J.G., Kimionis, J. and Tentzeris, M.M. (2017) 'Printed motes for IoT wireless networks: State of the art, challenges, and outlooks', *IEEE Transactions on Microwave Theory and Techniques*, Vol. 65, No. 5, pp.1819–1830.

Huang, Y., Tang, B., Deng, L. and Zhao, C. (2020) 'Fuzzy analytic hierarchy process-based balanced topology control of wireless sensor networks for machine vibration monitoring', *IEEE Sensors Journal*, 13 January, Vol. 20, No. 15, pp.8256–8264.

Iwendi, C., Maddikunta, P.K.R., Gadekallu, T.R., Lakshmanna, K., Bashir, A.K. and Piran, M.J. (2021) 'A metaheuristic optimization approach for energy efficiency in the IoT networks', *Software: Practice and Experience*, Vol. 51, No. 12, pp.2558–2571.

Jerbi, W., Guermazi, A. and Trabelsi, H. (2019) 'Orphan node connected management in multi-hop clustering-based routing protocols for wireless sensor networks', *International Journal of Interdisciplinary Telecommunications and Networking (IJITN)*, Vol. 11, No. 4, pp.1–16.

Kang, B. and Choo, H. (2018) 'An energy-efficient routing scheme by using GPS information for wireless sensor networks', *International Journal of Sensor Networks*, Vol. 26, No. 2, pp.136–143.

Kaya, S.K., Paksoy, T. and Garza-Reyes, J.A. (2020) 'The impact of the internet of things on supply chain 4.0: a review and bibliometric analysis', *Logistics 4.0*, pp.35–50.

Khedr, A.M., Aziz, A. and Osamy, W. (2021) 'Successors of PEGASIS protocol: a comprehensive survey', *Computer Science Review*, February, Vol. 1, No. 39, p.100368.

Kumar, R. and Mathur, R. (2017) 'D-BEENISH: distance incorporated balanced energy efficient network integrated super heterogeneous protocol for WSN', *International Journal of Systems, Control and Communications*, Vol. 8, No. 3, pp.187–203.

Natesan, S. and Krishnan, R. (2020) 'FLCEER: fuzzy logic cluster-based energy efficient routing protocol for underwater acoustic sensor network', *International Journal of Information Technology and Web Engineering (IJITWE)*, Vol. 15, No. 3, pp.76–101.

Preeth, S.S., Dhanalakshmi, R., Kumar, R. and Shakeel, P.M. (2018) 'An adaptive fuzzy rule based energy efficient clustering and immune-inspired routing protocol for WSN-assisted IoT system', *Journal of Ambient Intelligence and Humanized Computing*, December, Vol. 17, pp.1–3.

Ramadhan, F. and Munadi, R. (2021) 'Modified combined LEACH and PEGASIS routing protocol for energy efficiency in IoT network', in *2021 International Seminar on Application for Technology of Information and Communication (iSemantic),* September, Vol. 18, pp.389–394, IEEE.

Shukla, A. and Tripathi, S. (2020) 'An effective relay node selection technique for energy efficient wsn-assisted IoT', *Wireless Personal Communications*, Vol. 112, No. 4, pp.2611–2641.

Singh, O. and Rishiwal, V. (2020) 'Scalable energy efficient routing mechanism prolonging network lifetime in wireless sensor networks', *International Journal of Systems, Control and Communications*, Vol. 11, No. 2, pp.161–177.

Slimani, A., Redjimi, M. and Slimani, D. (2020) 'An agent-based cluster head management strategy for hierarchical wireless sensor network', *International Journal of Systems, Control and Communications*, Vol. 11, No. 4, pp.321–333.

Sujanthi, S. and Kalyani, S.N. (2020) 'SecDL: QoS-aware secure deep learning approach for dynamic cluster-based routing in WSN assisted IoT', *Wireless Personal Communications*, October, Vol. 114, No. 3, pp.2135-2169.

Thomas, D., Shankaran, R., Orgun, M.A. and Mukhopadhyay, S.C. (2021) 'SEC 2: a secure and energy efficient barrier coverage scheduling for WSN-based IoT applications', *IEEE Transactions on Green Communications and Networking*, Vol. 5, No. 2, pp.622–634.

Wang, Z., Qin, X. and Liu, B. (2018) 'An energy-efficient clustering routing algorithm for WSN-assisted IoT', in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, April, pp.1–6, IEEE.

Wu, X., Cho, J., d'Auriol, B.J. and Lee, S. (2007) 'Energy-aware routing for wireless sensor networks by AHP', in *IFIP International Workshop on Software Technolgies for Embedded and Ubiquitous Systems*, May, Vol. 7, pp.446–455, Springer, Berlin, Heidelberg.