ENERGY EFFICIENT DATA TRANSMISSION MODEL FOR INTERENT OF THINGS APPLICATION

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Abstract: The elementary operation of IoT are data sensing, collection and transmission; the observed value of sensed data from the sensor device are transmitted toward intermediate/sink device in a periodic manner for smart decision making in timely manner. Improving lifetime performance and network reliability for collecting sensed data is the major objectives of IoT enabled sensor network (IoT-SN). Along with, achieving minimal latency and improving energy efficiency is a major performance metric for provisioning IoT-SN. This work presents energy efficient data transmission (EEDT) model adopting cross layer design for provisioning Internet of things application. Experiment outcome shows EEDT model achieves superior outcome when compared with existing data transmission model in terms of improving energy efficiency, communication overhead and packet processing latency reduction.

Key words: Clustering, Cross Layer Design, Energy Efficiency, IoT, Routing.

1. INTRODUCTION

IoT system enables services to end client by connecting through millions of interconnected smart devices that shares sensory and computational data. IoT is composed of various kinds of interconnected nodes and systems that can be large or small deployment. Vehicular network, mobile network, sensor network, and other wireless access network will be seamlessly interconnected together for provisioning smart infotainment applications service to end clients. Device to device communication is considered to be key element of IoT where the device is equipped with sensor and actuator for collecting and transmitting information. In particular thousands of devices are deployed across network area for carrying out sensing and surveillance activity. The key component of device-to-device communication is location centric D2D event triggering, low energy dissipation, preference aware event monitoring, low mobility, time controlled information communication, packet switching, and low mobility. Additionally, for any device-to-device applications sensing and communication nodes are the necessary endpoints. Nonetheless, without support of wireless personal area network technologies for example Bluetooth, ZigBee, and 6LoWPAN the endpoints cannot communicate directly with interconnected device or wireless communication network. Nonetheless, energy management of sensor network device are needed for wide adoption of these technologies, especially choosing right network routing mechanism play very important role in extending battery energy efficiency. This work assumes that in future IoT applications includes billions of actuator, tiny sensor devices, and other device are interconnected to form a self-organized and self-governed wireless communication environments without need of any human intervention. These IoT device will aid in improving quality of living of humans being in daily lives activities.

2. LITERATURE SURVEY

Reducing energy dissipation and improve lifetime of system is the main objective of network routing management in wireless machine-to-machine communication systems. In [1] presented LEACH (Low energy adaptive clustering hierarchy) routing design for WSN for improving energy efficiency of sensor node. The model showed benefit of using cluster-based routing rather than hop-based transmission. Nonetheless, as the size of network increases the LEACH protocol provides very poor result, i.e., they are not suitable for large network. This is because the CH (cluster head) closer to sink/gateway suffers from energy overhead. Thus, preserving energy in IoT enabled sensor network is a major focus for existing researchers. The energy efficient routing models for machine-to-machine sensor network are classified into hop-based and cluster-based routing model.

In [2] presented a fuzzy based clustering-based routing methodology for enhancing energy efficiency performance of larger WSN. However, similar to LEACH the model induce energy overhead among CH closer to the gateway node. To address [3] modeled a clustered based routing design for WSN using type-2 Fuzzy Logic (T2FL). The model distributed load among sensor device aiding WSN lifetime performance. However, the cluster-based routing methodology is modelled under homogenous communication environment. However, this model cannot provide real-time heterogeneity performance prerequisite of modern IoT enabled sensor network applications. Therefore, efficient routing methodologies are needed for meeting IoT application real-time prerequisite. In [4] modelled data collection scheme, to process data [5] presented efficient clustering technique and [6] modelled information prediction technique for cluster-based network. The model [4, 5], and [6] minimized energy dissipation of IoT nodes; nonetheless they did not consider addressing data transmission latency. For minimizing latency [7] adopted evolutionary computing for cluster formation; nonetheless induce computational overhead among sensor device. As a result, sensor device dies much early resulting in loss of connectivity in IoT network. In [8] modelled a routing methodology for heterogeneous WSN [10] that route packets to node toward gateway hub with less packet loss and energy consumption; nonetheless, did not addressed data transmission latency minimization problem under heterogeneous IoT enabled sensor network. Thus, for reducing data access latency and meeting energy constraint of sensor network number of models has been presented in [11-14]. In [15] presented fuzzy based cluster head selection and in [27] adopted multipath based transmission scheme. Both [15] and [16] achieved good result when compared with existing data transmission scheme. In [17], they have formulated an energy- effective routing algorithm. In this algorithm the resource allocation problem in each hop of the path is changed to some equivalent's convex optimization issues, which are settled by means of double decay. In [18], the investigation of Butterfly Optimization Algorithm (BOA) is utilized to check the ideal head bunch head from various gathering of hubs. In [19], the paper proposes a scientific categorization for the grouping of existing progressive steering conventions for WSNs and examines the usefulness and execution of existing various levelled directing algorithms. In [20], Optimal Cluster-Based Routing (Optimal-CBR), the energy effectiveness, and organization lifetime are further developed utilizing a progressive steering approach for applications on the IoT in the 5G climate and past. In [21], an original direction planning technique dependent on inclusion rate for different versatile sinks is introduced particularly for enormous scope WSNs. A further developed molecule swarm advancement (PSO) joined with transformation administrator is acquainted with search the stopping positions with ideal inclusion rate. However, did not considered dynamic varying nature of environmental condition [22]. Thus, result in improper scheduling leading to packet loss and loss of energy.

For overcoming research problems this work present a cross layer routing design for building energy efficient data transmission (EEDT) model for IoT enabled wireless sensor network. First, EEDT model deploy sensor device across IoT enabled wireless sensor network. Then the position of each device and its adjacent device are obtained using received signal strength. Second, the EEDT model present an efficient method for selecting cluster head that balance energy efficiency and improves network coverage. Third, present a probabilistic model for estimating packet loss within network and optimize the TDMA schedule for collecting packet in IoT enabled WSN. Lastly, transmit the packet with minimal energy consumption, a smaller number of hops and less packet failure route.

The main contribution of this work is as follows.

- Presented cross layer design for routing data in IoT enabled WSN.
- Presented CH selection method that improves energy efficiency and network coverage.
- MAC schedule is optimized based on current packet failure probability in dynamic manner. Packets are routed considering multi-objective parameter with minimal path, less latency with better energy efficacy.

3. ENERGY EFFICIENT DATA TRANSMISSION MODEL FOR INTERNET OF THINGS APPLICATIONS

Here the IoT device are embedded with temperature sensor which are powered by battery for carrying out sensing operation. Further, the IoT device are placed randomly across sensing region and transmit sensed information to the edge device which act as a gateway server toward cloud computing environment for further analysis. For improving energy efficiency of IoT enabled network this work use cluster based communication. The cluster based communication is composed of two phase. First, intra cluster communication phase where IoT device will communicate with its cluster head IoT device. Second, inter cluster communication phase, the cluster head IoT device will transmit packet to its nearby cluster head IoT device towards edge broker.

Cluster head selection: In traditional model the cluster head device is selected based on threshold parameter. For example, in LEACH the cluster head is chosen considering IoT device with highest energy on particular instance of time (i.e., rounds). However, using existing cluster head scheme are not efficient in improving network coverage. Thus, affecting lifetime of IoT applications service. This is because in general the IoT device are deployed in random manner where some area will be denser where multiple overlapping devices will co exit and some areas are not denser where only one or two devices will be overlapping. For improving network coverage and lifetime of network this work present an improved threshold model for selection of cluster head.

First this work computes the overlapping IoT device distance p, where $0 \leq p \leq 2P$ apart from each other as follows

$$O_F = 2P^2 \left[\theta - \frac{p}{2P} \sqrt{1 - \left(\frac{p}{2P}\right)^2} \right] \quad (1)$$

where θ can be estimated using following equation

$$\theta = \cos^{-1}(p/2P) \quad (2)$$

The normalized overlapping section of IoT device is obtained using following equation

$$\omega = O_F/\pi P^2 = 2\left[\cos^{-1}(r) - r\sqrt{1 - r^2}\right]/\pi \quad (3)$$

where ω will be within 0 and 1, $0 \leq r \leq 1$ and r depicts the mean ratio of CH IoT device with respect to IoT device considering particular interval of time. The r is computed using following equation

$$r = p/2p \quad (4)$$

For improving CH selection and enhance the lifetime and network coverage of IoT network this work gives different probability to different IoT device for being CH. This probability value will rely on normalized active coverage area with respect with maximum coverage region of respective IoT device. The active coverage area is described as the ration of active coverage area with respect to maximum coverage area of respective IoT device. Thus, the normalized active coverage area of IoT devices can be computed as follows

$$\mu = \mu_0 + \sum_{n=1}^{\infty} \frac{\mu_n}{n+1}. \quad (5)$$

In above equation μ will be range of $(0,1)$. When the value of μ is 1, then there are is no overlapped device for particular IoT device. Similarly, if the value of μ is less than 1, then there are multiple overlapping IoT device for particular IoT device. Further, for obtaining normalized active coverage area of IoT device in network in energy efficient manner this work establishing equivalent distance $\bar{P}$ using mean signal strength received R_p from adjacent device. This process is done during deployment process by exchanging a hello message. Subsequently, this work obtains normalized overlapping area $\omega(d)$ for IoT device d using Eq. (1), and $r = \bar{P}/2P$. Then using Eq. (3), the normalized active coverage area can be established using following equation

$$\mu(d) = \mu_0 + \frac{\mu_1}{2} = [1 - \omega(d)] + \frac{\omega(d)}{2} = 1 - \frac{\omega(d)}{2} \quad (6)$$

Using Eq. (6) will aid assuring less probability will be given to IoT device for being cluster head with higher $\mu(d)$. Similarly, higher probability will be given to IoT device for being cluster head with lower $\mu(d)$. Therefore, this work changes the parameter r by considering r as parameter that is proportional with respect to IoT device d normalized overlapping coverage area as described below

$$r(d) = \propto \times\, \omega(d) \quad (7)$$

where $\propto$ represent the average size of CH. Therefore, the improved threshold parameter $H(d)$ for selecting CH IoT device d is established using following equation

$$H(d) = \begin{cases} \dfrac{r(d)}{1 - r(d) \times [\varphi mod(1/r(d))]}, & if\ d \in \bar{S} \\ 0, & Otherwise. \end{cases} \quad (8)$$

where $\varphi, 0 \le \varphi < \infty$, depicts the present session instance (i.e., round), $\bar{S}$ depicts the set of IoT device which have not been as a CH yet for certain session instance of time, d depicts the CH for current session instance $1/r(d)$. In this manner in each round the IoT devices are elected as CH with different probabilities. Using Eq. (8), the IoT device with smaller $\mu(d)$ will be given higher probabilities (i.e., higher $r(d)$) being CH with short interval of time. Similarly, the IoT device with higher $\mu(d)$ will be given lesser probabilities being CH with higher interval of time. Further, it is noted that higher $\mu(d)$ improves energy efficiency and smaller $\mu(d)$ induces overhead for being CH. From this it can be seen the proposed CH selection method using normalized active coverage area enhance the performance of IoT network. After electing cluster heads, each member IoT devices will communicate with respective cluster head IoT device on a given slot time using Time Division Medium Access. Further, keeping sensor device active all the time induces energy overhead.

Thus, only few numbers of IoT device will be active at the time within IoT network. Thus, may affect the packet transmission performance. Therefore, this work computes the packet failure probability and brings good tradeoffs to achieve better transmission with minimal energy dissipation and less latency. The packet failure probability will depend on number of neighbors the cluster head will have, which can be computed as follows

$$\mathcal{F}_d(d) = (\delta\pi S^2)^d e^{-\gamma\pi S^2}/\delta!\,,\ \ \delta = 0,1,2,3,\dots\infty \tag{9}$$

Let us assume that all the member device will decode packet successfully and the received Signal to Noise Ratio (SNR) $\gamma_{,}$ at distance s from the CH IoT device under Rayleigh fading channel can be obtained using following equation

$$\gamma_{,} = \mathcal{G}D_{,}|c|^2/s^2\mathcal{N}_0 \tag{10}$$

where $\mathcal{G}$ can be computed using following equation

$$\mathcal{G} = \frac{(\mathcal{G}_{Tr}\mathcal{G}_{Re}\lambda^2)}{(L_m F_n(4\pi)^2)} \tag{11}$$

where $D_{,}$ depicts per bit energy dissipation of intra cluster communication, $|c|$ depicts Rayleigh distribution (i.e., the channel gain between transmitter and receiving device (i.e., cluster head), $\mathcal{N}_0$ represent the Gaussian noise power at receiving device, λ depict carrier wavelength, $\mathcal{G}_{Tr}$ depicts the sender antenna gain, $\mathcal{G}_{Re}$ represent receiver antenna gain, $L_m$depicts additive noise of IoT devices, and $F_n$describes the receiver noise parameter. Therefore, the mean bit error rate (BER) for respective s and $D_{,}$ can be established using following equation

$$L_{,}^{b} = D\big(\mathbb{Q}(2\gamma_{,})\big) \cong {s^2\mathcal{N}_0}\big/{4\mathcal{G}D_{,}} \tag{12}$$

where $D(\cdot)$ describe the mean parameter corresponding to distribution of $|c|$ and $\mathbb{Q}(y)$represent Q-function, which can be computed using following equation

$$\mathbb{Q}(y) = \left(\frac{1}{\sqrt{2\pi}}\right)\int_{y}^{\infty} e^{-x^2/2}\,dx \tag{13}$$

Let B describe the packet size. Thus, the packet failure probability $L_{,}^{p}$ can obtained using following equation

$$L_{,}^{p} = 1 - \left(1 - L_{,}^{b}\right)^B \tag{14}$$

Further, the s among CH's and its respective cluster head respective neighbouring IoT device within each cluster, the probability density function can be estimated using following equation

$$\mathcal{F}_s(s) = \frac{2s}{S_{,}^2}, S_{,} \geq s > 0 \tag{15}$$

As $L_{,}^{b}$ is generally very small, thus this work considers $1 - \left(1 - L_{,}^{b}\right)^B \cong BL_{,}^{b}$. Thus, using Eq. (14) and Eq. (15) the average packet failure probability within cluster and among cluster head can be obtained using following equation

$$\vec{L}_{\prime}^{p} \cong \int_{0}^{S_1} B\left({s^2\mathcal{N}_0}/{4\mathcal{G}D_{\prime}}\right){2s}/{S_{\prime}^2}\,ds = {B\mathcal{N}_0 S_{\prime}^2}/{8\mathcal{G}D_{\prime}} \quad (16)$$

After electing cluster head and obtaining packet failure probability, next this work establishes efficient routing path $L_{\mathcal{M}}$ that minimize energy dissipation with less latency using following equation

$$L_{\mathcal{M}} = \mathcal{E}_v + \mathcal{G}_l + \bar{\mathcal{G}}_l + \vec{L}_{\prime}^{p} \quad (17)$$

where $\mathcal{E}_v$ depicts residual energy of each IoT device which can be computed using first order transceiver energy model, $\mathcal{G}_l$ describe the predictable hop size, and $\bar{\mathcal{G}}_l$ describe inverse of predictable hop size. The proposed energy efficient data transmission model minimizes latency and energy dissipation for transmitting packet in IoT network.

4. SIMULATION ANALYSIS AND RESULTS

The system environment considered for experimental studies are as follows. Experiment is conducted on Intel quad core processor with 8 GB RAM on Windows 10 operating system. The results have been simulated using the SENSORIA simulator is considered for experimental study. The algorithm of proposed EEDT and LEACH is modelled using C++ and C# programing language. The parameter considered for evaluating performance of EEDT and LEACH through simulation study is shown in Table 1.

Table 1. Network parameter configuration used for performance analysis of EEDT and LEACH

Parameter	Value
IoT enabled WSN area	$50 meters \times 50 meters$
Number of IoT communication gateway	1
Number of IoT devices	$500\ to\ 1000$
Transmission range of each IoT device	$5\ meters$
Sensing range of each IoT device	$3\ meters$
Initial energy of each IoT devices	$0.1 - 0.2\ Joules\ (j)$
Radio energy dissipation of IoT devices	$50\ nj/bit$
IoT environment control packets length	$248\ bits$
IoT environment data packets length	$2000\ bits$
IoT environment data transmission speed	$100\ bit/seconds$
IoT environment bandwidth	$10000\ bit/seconds$
IoT environment sensing event time	$0.1 seconds$
Types of IoT device used for sensing environment	Temperature
IoT environment Idle phase energy consumption ($Eelec$)	$50\ nj/bit$
IoT environment signal amplification energy (Emp)	$100\ pJ/bit/m2$

4.1. Internet of things Enabled Sensor network Lifetime Performance Evaluation

Here experiments are carried out for evaluating network lifetime performance of EEDT over LEACH. Two case study is considered for evaluating network lifetime performance. In first case network lifetime performance is evaluated in terms of total IoT device death. The network lifetime performance evaluation is carried out by varying the IoT device considering fixed network area as shown in Figure1. A lifetime performance improvement of 68.37%, 76.65%, 83.17%, 84.12%, 84.06% and 85.28% is achieved by EEDT over LEACH considering 500, 600, 700, 800, 900 and 1000 IoT nodes, respectively. The EEDT improves energy efficiency of IoT enabled sensor network by 80.27% on an average considering varied IoT device configuration over LEACH routing model. From Figure1, it can be stated when IoT device density are increased the LEACH lifetime performance decreases whereas the EEDT is stable irrespective of IoT device size. In second case, network lifetime performance is evaluated in terms of first IoT device death. The network lifetime performance evaluation is carried out by varying the IoT device considering fixed network area as shown in Figure 2.

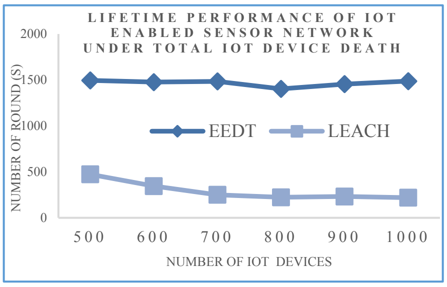

Figure 1. IoT-SN lifetime outcome under varied IoT device considering Total IoT Death

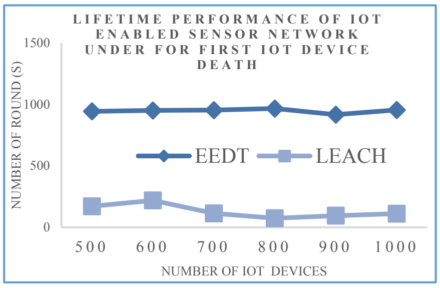

Figure 2. IoT-SN lifetime outcome under varied IoT device considering First IoT Death

A lifetime performance improvement of 81.89%, 76.98%, 88.06%, 92.35%, 89.65% and 88.378% is achieved by EEDT over LEACH considering 500, 600, 700, 800, 900 and 1000 IoT devices respectively. The EEDT improves energy efficiency of IoT enabled sensor network by 86.22% on an average considering varied IoT device configuration over LEACH routing model. From Fig. 2 it can be stated when IoT device density is increased the LEACH lifetime performance decreases whereas the EEDT is stable irrespective of IoT device size.

4.2. Internet of Things Sensor Network Communication Overhead Performance Analysis

Experiments are conducted to evaluate the network communication overhead performance of proposed EEDT over LEACH. The network communication overhead performance evaluation is carried out by varying the IoT device considering fixed network area as shown in Fig. 3. A communication overhead reduction of 16.81%, 9.01%, 39.78%, 34.39%, 40.57% and 51.54% is achieved by EEDT over LEACH considering 500, 600, 700, 800, 900 and 1000 IoT devices respectively. The EEDT reduces communication overhead of IoT enabled sensor network by 32.03% on an average considering varied IoT device configuration over LEACH routing model. It can be seen from Figure 3 when IoT device density are increased both EEDT and LEACH communication overhead increases.

4.3. Internet of Things Sensor Network Data Processing Latency Performance Analysis

Experiments are conducted to evaluate the network data processing latency overhead performance of proposed EEDT over LEACH. The network data processing latency performance evaluation is carried out by varying the IoT device considering fixed network area as shown in Figure 4.

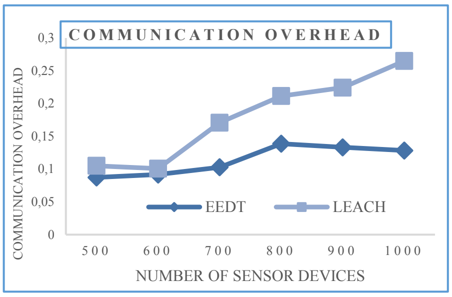

Figure 3. Communication overhead performance analysis considering varied IoT devices

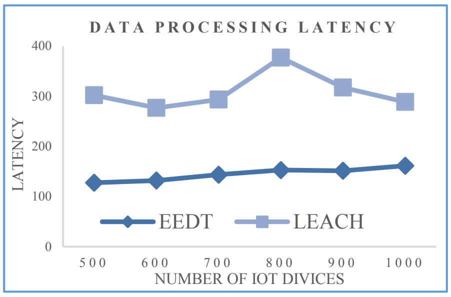

Figure 4. Data processing latency performance analysis considering varied IoT devices

A data processing latency reduction of 57.76%, 52.34%, 51.05%, 59.46%, 52.28% and 51.54% is achieved by EEDT over LEACH considering 500, 600, 700, 800, 900 and 1000 IoT devices, respectively. The EEDT reduces communication latency of IoT enabled sensor network by 52.83% on an average considering varied IoT device configuration over LEACH routing model.

4.4. Comparative Analysis of EEDT over State-of-art Routing Methodologies for IoT enabled Sensor Network

The outcome achieved by EEDT and various other recent routing methodologies over leach protocol is shown in Table 2 and 3 considering first IoT device death and Total IoT device death, respectively. From Table 2 and 3 it can be seen EEDT model achieves much better lifetime performance when compared with existing routing methodologies [2, 3, 7, 8, 9, 15, 16]. From result attained it is seen the EEDT model improves network coverage irrespective IoT device density under heterogeneous IoT enabled sensor network.

Table 2. EEDT and existing routing methodologies network performance improvement over LEACH under first IoT device death

Algorithm	Lifetime performance over *LEACH* routing methodologies
Fuzzy Logic Based Clustering [7]	56.7%
EEDT [Proposed Model]	86.22%

Table 3. EEDT and existing routing methodologies network lifetime performance improvement over LEACH under Total IoT device death

Algorithm	Lifetime performance over *LEACH* routing methodologies
Fuzzy logic-based clustering [7]	25.0%
Energy efficient clustering algorithm using type 2 fuzzy [8]	50.0%
Self-organizing CH selection model [16]	55.0%
Cluster tree topology [18]	44.0%
Energy efficient reliable routing [9]	15.0%
PFuzzyACO [21]	36.48%
Multipath data transmission using fuzzy and cat swarm optimization [22]	80.27%
EEDT[Proposed Model]	80.27

5. CONCLUSION

Minimizing energy consumption of sensor device is most desired. Many approaches has been presented in recent times to minimize energy consumption. This work presents EEDT adopting cross layer design. The EEDT model improves energy efficiency of IoT enabled WSN with less latency and computation overhead. Considering first IoT device death, an average energy efficiency improvement of 80.27% is achieved by EEDT over LEACH and considering total IoT device death average energy efficiency improvement of 86.22% is achieved by EEDT over LEACH. Further, EEDT model improve energy efficiency by 13.92% over multipath data transmission using fuzzy and cat swarm optimization model. The EEDT reduces communication overhead and data access latency by 32.03% and 52.83%, respectively over LEACH protocol. The overall result achieved shows the efficiency of EEDT over state of-art model Fuzzy logic based clustering [2], Energy efficient clustering algorithm using type 2 fuzzy [3], Self-organizing CH selection model [7], Cluster tree topology Energy efficient reliable routing [18], Energy efficient reliable routing [9], PFuzzyACO [15], Multipath data transmission using fuzzy and cat swarm optimization [16]. The future work would consider performance evaluation considering other network parameters and would considering provisioning real-time workload scheduling adopting cloud computing environment and provide simple security model for EEDT.

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Manuscript received on 30 January 2022