Original Article

Ensemble Learning Based Multiple Mobile Sink Architecture For Energy Efficient Wireless Body Area Network Towards Disease Centric Patient Group Data Management

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DOI: 10.47750/pnr.2022.13.S09.836

Abstract

In critical medical emergency situations, wireless sensor network employed for health care industry is termed as wireless body area network (WBAN). It is equipped as health monitoring systems which transmits the data packets containing critical information of patients' health. Therefore, to manage the increased traffic load and to provide ubiquitous medical services for highly prioritized disease, a new model for a disease-centric health-care management system using wireless body area networks (WBAN) in the presence of multiple health-cloud service providers (H-CSP) as multiple mobile sink has to be constructed on utilizing the theory of Social Network Analysis (SNA). It is adopted to optimize the computational complexity and the traffic load of the network in an area, considering different disease types and the criticality indices of the WBANs. Disease-centric Patient Group (DPG) formation among coexisting WBANs ensures optimized traffic load and reduced computational complexity. In this addition, we formulate a pricing model for the efficient mapping of critical WBANs from a DPG to an H-CSP to optimize the expected packet delivery delay and the network throughput for energy efficient data communications. Consequently, to identify the critical WBANs from a DPG, we design an ensemble learning to identify a decision parameter based on an assortment of selection parameters of multiple mobile sinks. The selection of parameters from the multiple mobile sink provides optimized solution for traffic load and energy efficiency of the resources. The performance of the Efficient Healthcare Management (HCM) scheme is analyzed based on distinct measures such as Packet delivery ratio, delay, and throughput. Simulation results exhibit significant improvement in the network performance over the existing schemes.

Keywords: Wireless Body Area Network, Social Network Analysis, Traffic Analysis, Energy Efficient, Quality of service

1. Introduction

Healthcare in modern days has been undergoing crucial changes, as the common practice of clinical treatment is gradually being overhauled by ubiquitous healthcare systems. Cloud-assisted WBAN is an infrastructural and systematic integration of traditional WBAN with cloud. Cloud-assisted WBAN architecture provides cost-effective and real-time services to the affected victims. A WBAN comprises of multiple heterogeneous body sensor devices which are capable of monitoring different health attributes, record it in the form of raw health-data, and subsequently transmit the data to a local data processing unit[1]. The body sensors located in the vicinity of human tissue sense the physiological signals of the patients, process them, and then send the sensed information to the Local Processing Unit[2].

The LPU sends the medical data to the servers through the local APs for analysis by the medical prediction system. Increased number of WBANs in a specific area degrades the performance of each WBAN in terms of end- to- end packet delivery delay and network throughput. Therefore, the management of increased traffic load of WBANs is a major challenge, as each WBAN carries sensitive medical data[3].

In conventional multi sink WBAN architecture, medical data specific to a particular disease is dedicatedly stored in a particular server to manage the data efficiently. Therefore, when specific disease affected patients are not present in that particular category, then these servers become unutilized and the network management cost increases. In this context, the integration of cloud services to a WBAN platform provides cost effective, elastic and real-time healthcare services using unsupervised constraints. In normal situations, resource demand from each WBAN may differ, which may even increase during emergencies. Due to the fact that different disease-specific WBANs demand different kinds of services, each such WBAN needs to choose an optimal H-CSP among heterogeneous cloud service providers[4].

In this work, traffic load minimization and selection of an optimal H-CSP pricing policy for heterogeneous WBANs in a cloud enabled Platform has been modelled. The model generates resource optimization n the optimal mapping of critical WBANs to a particular H-CSP among several heterogeneous H-CSPs due to sharing of resources and reduction in the overall cost of Usage. It also maintains the energy efficiency of each WBAN belonging to a particular DPG in the presence of heterogeneous H-CSP[5].

The manuscript is organized as follows. In Section 2, we crisply discuss the existing works on cloud-assisted WBANs. Section 3 describes the system and mathematical model of the proposed scheme. In Section 4, we propose an optimization problem for energy-efficient social relation grouping to optimize the traffic load of WBANs. Section 5 presents the optimal pricing policy in the presence of heterogeneous H-CSPs. Section 6 presents the simulation results and Section7 discuss the conclusion and future works.

2. Related works

In this section, more traditional model of WBAN has been analysed in detail on both online and offline data streams. The techniques are as follows

2.1. Cloudlet-Based Efficient Data Collection in Wireless Body Area Networks

Cloudlet-based efficient data collection system is to have a large scale of monitored data of WBANs to be available at the end user or to the service provider in reliable manner. A prototype of WBANs, including Virtual Machine (VM) and Virtualized Cloudlet (VC) has been proposed for simulation characterizing efficient data collection in WBANs. Using the prototype system, we provide a scalable storage and processing infrastructure for large scale WBANs system. This infrastructure will be efficiently able to handle the large size of data generated by the WBANs system, by storing these data and performing analysis operations on it. The proposed model is fully supporting for WBANs system mobility using cost effective communication technologies of WiFi and cellular which are supported by WBANs and VC systems[6].

2.2. Cooperative Dynamic eHealth Service Placement in Mobile Cloud Computing

Cooperative operation of Wireless Body Area Networks (WBANs) technology and Cloud Computing is providing effective management of Dynamic e-health data. It allows eHealth providers to deploy instantly and on demand their eHealth services to monitor people's health status. Cooperative strategy between a mobile operator and a cloud provider towards an efficient eHealth service placement in the cloud has been considered for managing the network throughput and latency[7].

3. Proposed Scheme

This section describes our system model and mathematical model of the proposed architecture of Wireless body area network.

3.1. System model

In WBAN architecture, N= {1, 2, 3...n} is considered as set of WBAN, B= {B_1, B2...B_n} considered as different zones of patient, M= {1, 2...m} is set of heterogeneous body sensor, P= {$p_{1,}p_2....p_m$} which represents the local processing unit to aggregate the heterogeneous medical data of the body sensor. Due to the heterogeneity of the body sensors, each such sensor has different bandwidth requirement, BW ε {BW_1,BW_2....BW_n} to transmit the data. Therefore each WBAN demands different aggregated bandwidths to transmit its data from a specific H-CSP. The Communication between the nodes has been carried out using convergecast model. The basic mathematical notation has been defined in the table 1

Table 1: Mathematical Notation of the Proposed Architecture

C_i	criticality indices of WBAN
T_i	Traffic load of each WBAN in a specific area
H	Throughput of each WBAN
G	WBAN groups
D	Proximity of WBANs from Access Points
t	Total Time duration of the particular instant
R	Data transmission Rate

During medical emergency, the total volume of WBANs in a particular area expends tremendously, which increases the traffic load of WBANs significantly. In the presence of increased traffic load the performance of WBANs decrease notably in terms of network throughput[8]. Therefore, to optimize the increased traffic load and maximize the network throughput, DPG has to be initiated. In the formation of DPG, the WBANs with criticality less than the threshold criticality C_i N threshold are not included in the same group. Threshold criticality C_i N varies based on the type of disease. After the formation of relation grouping, each group is mapped with a particular CSP. In the traditional WBAN architecture corresponding to a disease, a specific server is dedicated for processing. Therefore, if any disease-specific WBAN is absent in a particular hospital and then the server remains unutilized. In the presence of heterogeneous H-CSPs, a specific group-based WBAN selects an optimal HCSP, depending on the resource available, the total criticality of the WBAN, and the proximity of the AP. The figure 1 represents the architecture of the proposed model.

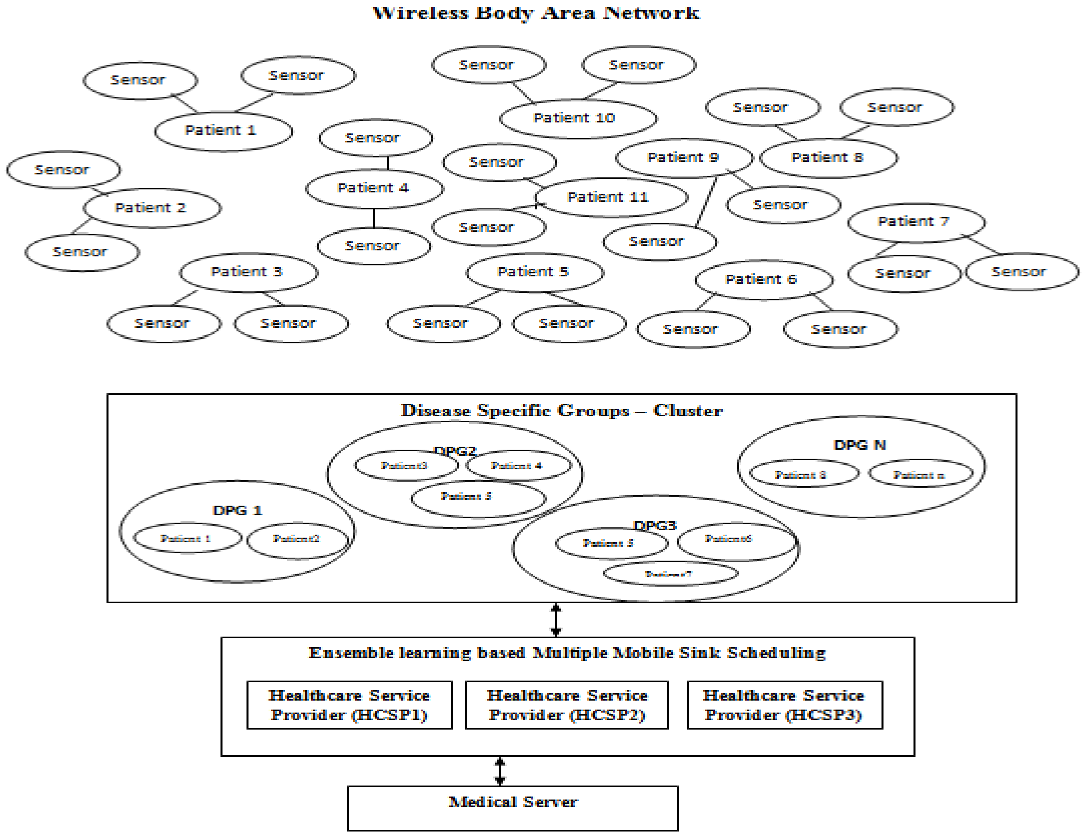

Figure 1: Architecture of the proposed model

In the architecture above, Ubiquitous health monitoring relies on some special characteristics of wireless body sensor nodes. The basic principle of these sensors is that the source of the signals received is the living tissue. These body sensors nodes are mounted on the patient's body to enable remote monitoring of health parameters. Each such sensor node is deployed to monitor a specific health parameter. For instance, a pulse oximeter measures the oxygen saturation level in blood and the heart rate, and an EKG sensor monitors and records the EKG-graph for a patient[9].

3.1.1. Disease Centric patient group

It composed of several WBAN depending on the distinct syndromes. The average no of WBAN present in DPG at time t with relation r is given by

Distinct syndromes $d=\{d_1,d_2.....d_n\}$

$$G=\{n_1^r, n_2^r.......n_t^r\}$$

The disease -centric relation among WBANs is obtained based on similar disease types, which is calculated using the n *n encounter matrix. Due to the mobility of WBANs, a WBAN Bi comes in contact with another WBAN Bj . During mutual connection, WBANs transfer its CI Φ and syndromes d with each other using beacon messages. The encounter matrix n*n is the count of contacts each WBAN encounters. The encounter matrix is defined as

$$W_{ij} = \begin{cases} 1 & \text{if } d_{Bi} \in d_{Bj} \\ 0 & \text{otherwise} \end{cases}$$

Where d_{Bi} and d_{Bj} denotes the syndromes of diseases respectively.

$$Aff\,(i,j) = \begin{cases} 1 & \text{if } B_i \text{ and } B_j \text{ encountered each other} \\ 0 & \text{otherwise} \end{cases}$$

3.2. Mathematical model

The mathematical model has been derived to measure the fitness parameter of the sensor unit and severity of disease towards priority setting. The parameter considered is energy dissipation factor, starvation factor and health data criticality factor. We discuss the importance of these factors in the formulation of the fitness parameter.

3.2.1. Energy Dissipation factor

Sensor nodes are, capacitated with limited amount of energy. It is crucially important to ensure that the rate of dissipation of energy can be minimized for these sensors. The popular sources to harvest energy for body sensors are movement of limbs, locomotion of the human, or even the human body temperature. The nodal energy dissipation factor (Edt;i) is defined as the maximum energy expended by the ith body sensor node after t timeslots is defined as the sum of the energy consumed due to sensing (Esn), transmissions (Etr), processing (Epr), and computations (Ecm) purposes, and the energy exhausted due to channel conditions (such as path fading, path loss, and BER) and, varied signal strength (Ech).

Energy Dissipation Factor ($E_{dt,i}$) = (E_{sn}*t)+E_{tr}*N + E_{pr}*n + E_{cm}(N-n)+E_{ch}

Where

n refers to the number of packets received

N refers to number of packet transmitted by a node during t slots

- **Sensing Energy**

Even body sensor nodes continuously monitor and record the concerned health parameter of a person over time, there is continuous drainage of energy in sensing[10]. The energy expended due to sensing in a single time-slot by each body sensor node is denoted as E_{sn}.

- **Transmission Energy**

The transmission energy of a body sensor node, E_{tr}, is the energy dissipated due to the transmission of a single data packet. The packet may be either originated from the node itself, or it could have reached the node as an intermediate hop towards its destination. E_{tr} usually has a higher magnitude, as broadcasting of health parameters in the form of packets requires considerable amount of energy.

- **Processing Energy**

In a WBAN, a body sensor node not only acts as a sensing device, but also as a routing device. As a part of intra-WBAN communications, each body sensor receives numerous data-packets from multiple other sensors, and route those data-packets further, either towards the destination anchor node, or towards another body sensor in its path, after processing the data packet[11]. Processing energy Epr of a body sensor is the energy expended due to processing of a single packet retrieved from the input-buffer, and subsequent mapping of the same to its destination through the routing table.

- **Communication Energy**

The energy consumed to perform preliminary computations on the raw sensed data before it is converted into a packet is termed as the computational energy of that node, and is denoted by Ecm. It is noted that the energy consumption due to computations is much less compared to the energy exhausted due to transmission of a data packet.

3.2.2. Pricing model

DPG formation among WBANs decreases the computational complexity and the traffic load of the network, it does not guarantee provisioning of QoS services to each WBAN. To manage QoS services among WBANs, the mapping of DPG to an optimal H-CSP is needed and the selection of critical WBAN from a DPG is also needed. Therefore, the selection of critical WBANs from a DPG is to be decided based on different selection parameters

$$V = \sum_{i=1}^{c} u_{ik}^{m} d_{ik}^{2} + \lambda(\sum_{i=1}^{c} u_{ik} - 1)$$

Where

u_{ik}^{m} is the Packet Criticality Rate

d_{ik}^{2} is the Packet generation rate

The total number of WBANs increases, then the network throughput decreases, and the traffic load in a particular area increases. To optimize the traffic load, WBANs, we need to estimate the effective traffic load using dynamic mobile sink velocity[12]. It is given by

$$v_{st} = \frac{\sum_{k=1}^{N} u_{ik}^{m} x_{kt}}{\sum_{k=1}^{N} u_{ik}^{m}}$$

Channel capacity constraints and potential congestion problems in the network are represented as the network throughput at time instant t is greater than the network throughput at time t -1 which increases the channel bandwidth based on the node priority.

$$\delta = I - D + \gamma . D_{EtoE}$$

Transmission delay

$$(D) = \sigma \times T_{AP}$$

Potential collision between route request propagated by neighboring nodes leads to packet delay. Potential congestion can eliminated using Potential energy saving of node which is given as follows

$$P_{saved} \geq \delta \times (P_{IDLE} - P_{SLEEP})$$

Increased traffic load and area significantly degrades the performance with respect to mapping cost and service rate, which can be resolved geographic fitness of the mobile sinks which acts as resources

$$Gf_j(R,t) = \frac{Availability(j,t)}{LF_j(R,t) \times Dist(j,R)}$$

Where

$$LF_j(R,t) = \max\{CPU_a, MEM_a, NBW_a, DBW_a\}$$

X_a is the ratio of requested resource

Available resource j. $0 \leq LF_j \leq 1$

3.3. Ensemble learning Based Multiple Mobile Sink Scheduling

Due to various internal and external factors, proposed WBAN can change dynamically, which impacts the localisation of nodes, delays, routing mechanisms, geographical coverage, cross-layer design, the quality of links, fault detection, and quality of service, among others due to pricing and priority models. In order to resolve those issues, ensemble learning has been employed to evaluate the pricing constraint, Priority Constraints, energy constraints and Traffic load constraints[13]. It helps to minimize the traffic load and high energy consumption of the mobile sinks and sensor nodes of WBAN. Multiple Diverse models have been trained for the routing characteristics of the mobile sinks using Heuristics Weighted Voting, Bagging and Boosting Combinations.

3.3.1. Heuristic weighted Sink Routing

Disease-centric cluster formation is carried to the node takes care of the total traffic of the WBANs in a particular area by forming DPG. It is achieved using Heuristic weighted constraints. In addition it cares of energy efficiency of the WBANs using cost efficient mapping. Heuristics weighted Voting is given by

$$h_{MAP} = \text{argmax}(M)_{h \in H}$$

Bagging Combination is given by Probabilities of likelihood for selection of the multiple mobile sink for data transmission with high throughput. The selection of critical WBAN from a DPG decided based on different selection parameters[14]. Consequently, the mapping of DPG to an optimal H-CSP is to be decided based on the pricing Model.The Probability of Bagging model is given by

$$P(h|D) = \mathrm{argmax}_{h\in H} P(D|h)P(h)/P(D) \propto \mathrm{argmax}_{h\in H} P(D|h)P(h)$$

Where

Boosting combinations learn the mean μ of the parameters of the mobile sink and traffic load of the network to generate the parameterized distributions with less variance. Due to the mobility of WBANs, each WBAN changes its region from one community to another, which significantly changes the QoS and bandwidth requirement of each WBAN. The increase in the criticality indices of WBANs also increases the packet generation rate of the body sensor nodes. It is given as

$$P(\mu|D,\sigma^2) = P(D|\mu,\sigma^2)P(\mu)/P(D) \propto P(D|\mu,\sigma^2)P(\mu)$$

Where $$\log(P(x|C_1)) = -\frac{1}{2}\log(2\pi) - \log(s_1) - \frac{(x_i - m_1)^2}{2s_1^2}$$

C1 and C2 is the different cluster for the mobile sink based on parameter.

Algorithm 1: Heuristic Weighted Multiple Mobile Sink Routing

Input: Number of WBANs (B_i ε B), criticality index ($Ø_t$) Data similarity index aff(i,j), relational
Output: Optimized traffic load T
Step1: Acquire information of all WBAN and Mobile sinks
Step2: Neighbor List generation using Energy and location constraints
Step3: Cluster Node ()
For (i= 1 to n)
Do Compute Node Traffic N_f
If (Node Traffic N_f < Available Bandwidth B_A)
Form Optimal Nodes for large Traffic
Else
Schedule the N_f to the Priority Node list
End for

Minimizing the empirical risk of the scheduling is the same as maximizing the likelihood of energy saving which is given by combination function. WBANs need increased bandwidth in order to transmit their data packets successfully[15]. As the available bandwidth does not fulfill the required bandwidth, there is a requirement of optimal mapping between WBANs and CSPs, in order to provide fair resources among WBANs with optimal price

$$c(x_i, y_i, f(x_i)) = -\log(P(y_i | x_i, f))$$

$$P(M | x) \propto P(x | M)P(M)$$

Where

P(x|M) is called the likelihood

P(M) is the prior probability of the traffic to the resource or mobile sink .

4. Simulation Results

In this Section, we simulate our proposed Ensemble learning based multiple mobile sink scheduling for energy efficiency on wireless Body Sensor Network using NS2 Simulator. Through extensive experiment, we demonstrate the properties and measure the network performance in terms of throughput, Packet delivery ratio, Network Overhead and packet loss. The proposed framework determines the node and sinks characteristics to generate the priority and pricing constraints to achieve energy efficient routing of WBAN for healthcare process[16]. In the Simulation, the set up of the network is described in the following table 2

Table 2-Simulation Parameters used to build a protocol

Simulation Parameter	**Value**

Simulator	NS2
Topology Size	1000m *1000m
Number of WBAN	200
Number of Mobile sinks	8
Bandwidth of the Network	2Mbps
Traffic type	CBR
Pause Time	10s,20s
Data Packet size	512 bytes
Buffer size	30 packets
Simulation Time	30 minutes
Velocity of Mobile sinks	1.5m/s

The Source node is selected randomly to transmit the data of size as mentioned previously in the table 1, it is initialized to send route request packet to base station or intermediate after every 10s through mobile sink. We considered the single-hop star topology for data transmission in WBANs, where each WBAN consists of 8 Mobile sink placed on the body. Transmission Path for the data transfer has been selected using neighbour list which computes node grouping against the node density and energy levels of the nodes.

Node traffic is produced with constant bit rate (CBR) on each health information transmission. The generation rate of the CBR is 150kb/s. To consider the varying traffic of WBANs in an area, the WBAN density factor which depends upon the node density has been varied. Also, traffic load from 500 Kbps to 950 Kbps has been varied to observe the mapping cost between WBANs and H-CSPs. Subsequently, the different data rates of body senor nodes have been considered [17].

The Node density is used to determine the capability nodes or data can be taken for data transmission. Node Density is calculated in order to avoid the data congestions in the network and is also used to choose the neighbour node of the network based on the energy constraint.

Node density = $= 1 + \frac{n*m}{m} + \frac{n(n-1)m}{m}$

Where

N is the no. of the node

M is the no of node supported by node N

Potential Connection PC = $\frac{n(n-1)}{2}$

The whole duration of mobile sink's moving trajectory on the path is divided into several consecutive time slots. The data collection hop count m = 3 is defined and use the Bayesian rule to find the effective path for large traffic. Energy consumption and efficiency of the data at different rates during transmission, reception, idle waiting and sleeping has been calculated under various heuristics considered for DPG. Finally IEEE 802.15.4 standard CSMA/CA access mechanism has been employed.

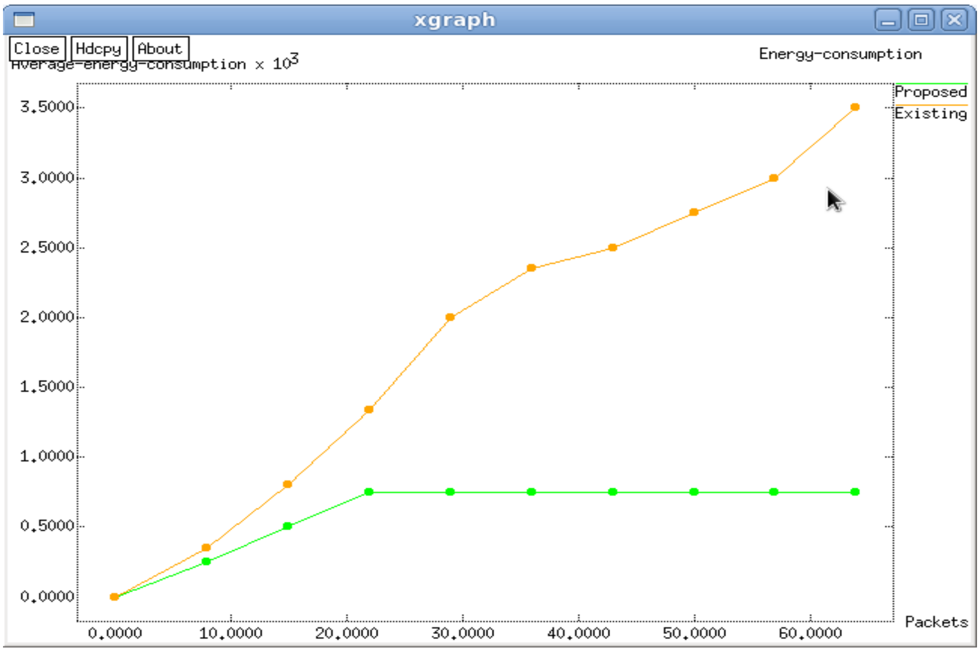

Figure 2: Performance Analysis of Proposed Framework against Existing Technique through Energy Utilization

The evaluation of the ensemble learning on multiple mobile sink data gathering and scheduling against the different network traffic is demonstrated and its comparison in terms of energy utilization and network utility of WBAN has been described on the increase of the number of HCSPs. The figure 2 represents performance evaluation. In order to achieve it, the critical WBANs form a DPG and are efficiently mapped to an optimal H-CSP.

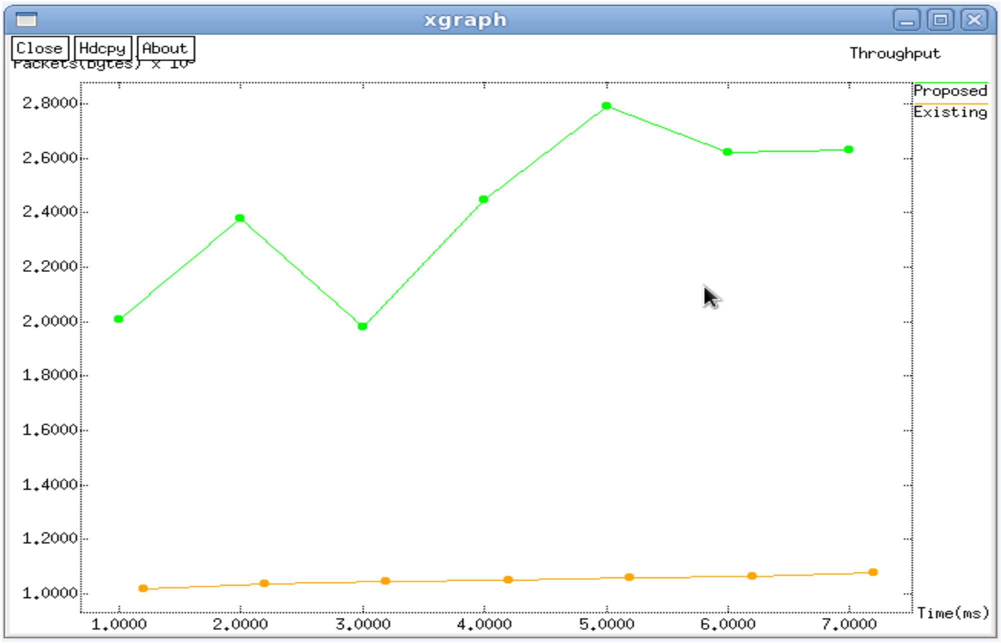

Figure 3: Performance Analysis of Proposed Framework against Existing Technique through Throughput

Therefore, the critical WBANs consume reduced energy than the normal WBANs, while transmitting the packets Energy utilization is important to ensure the perpetual operation of the network in the sense that no sensor would have drained its battery energy during data transmission.

The proposed model has been analysed against varying number of WBANs 100, 150, and 200 and varying number of H-CSPs 5, 10, and 15.On Increasing H-CSP, the critical WBAN can get improved services in the presence of multiple H-CSPs. The observations indicate that the proposed framework can find predict optimal states in short span of time in case of increase traffic load, throughput depends on the number of successful reception of packets at the sink. The proposed Ensemble learning based multiple mobile Sink Scheduling model on pricing and priority constraints is capable of identifying new data rate and new route by data forwarding paths. The figure 3 depicts the performance evaluation of the throughput.

Throughput = (Transmission Rate of the Mobile Sink)* Round Trip Time of Predicted path for Data Transmission

The WBANs from a DPG are efficiently mapped to the H-CSP, which maximizes the packet transmission rate. Consequently, as WBANs carry sensitive and important medical data packets, therefore it is necessary to increase the throughput of WBANs in efficient way, where proposed approach provides significant improvement in throughput for critical WBANs.

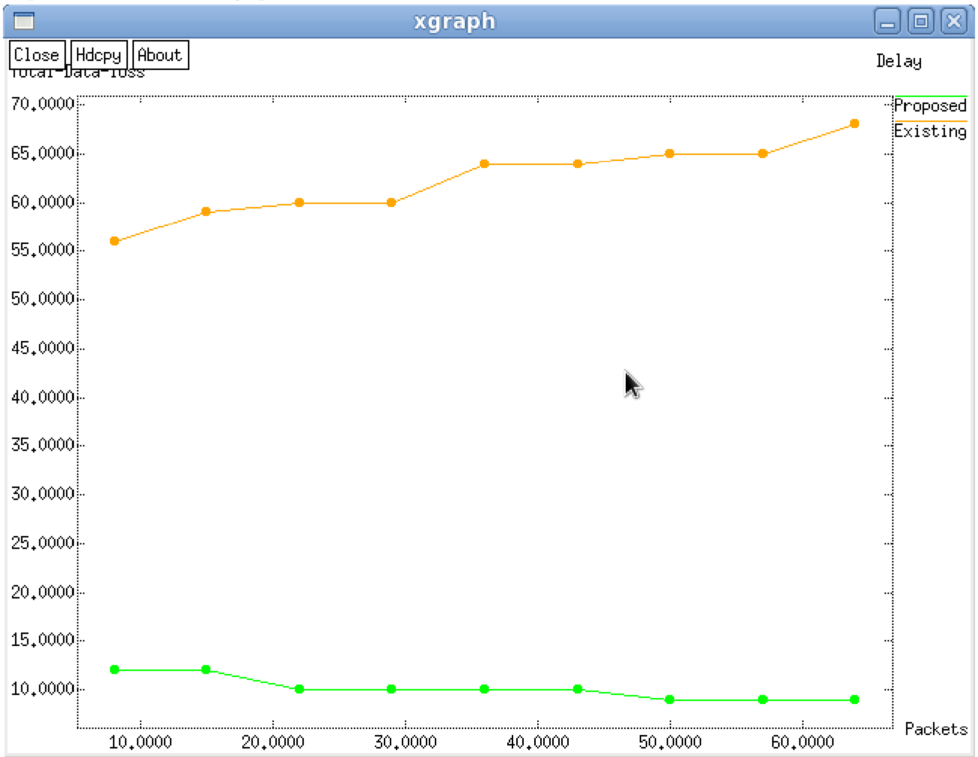

Figure 4: Performance Analysis of Proposed Framework against Existing Technique through Delay

On efficient mapping of critical WBANs to HCSP, each WBAN connects to optimal H-CSP, while preserving the QoS requirement and providing fair amount of resources. Therefore for the efficient mapping and data transmission, the HCM scheme consumes less energy. Table 2 concludes the performance values of the different metrics on evaluating the multiple mobile sink data collection for healthcare data.

Table 3 – Performance Evaluation of the different mechanism on Multiple Mobile Sink Scheduling against Various data traffic of the network

Technique	Throughput in mbps	Delay in mbps	Packet Delivery Ratio	Energy Consumption
CBDC Based WBAN- Existing	74.88	13.23	94.68	0.89 Joules

ELMMSS based WBAN- Proposed	84.76	8.89	99.91	34.89 Joules

Packet delivery ratio is defined as the ratio of the number of Sensor information successfully received by the destinations of the mobile. In another words, Packet delivery ratio defines the time duration between the data transmitted from the WBAN to the data received at the AP.

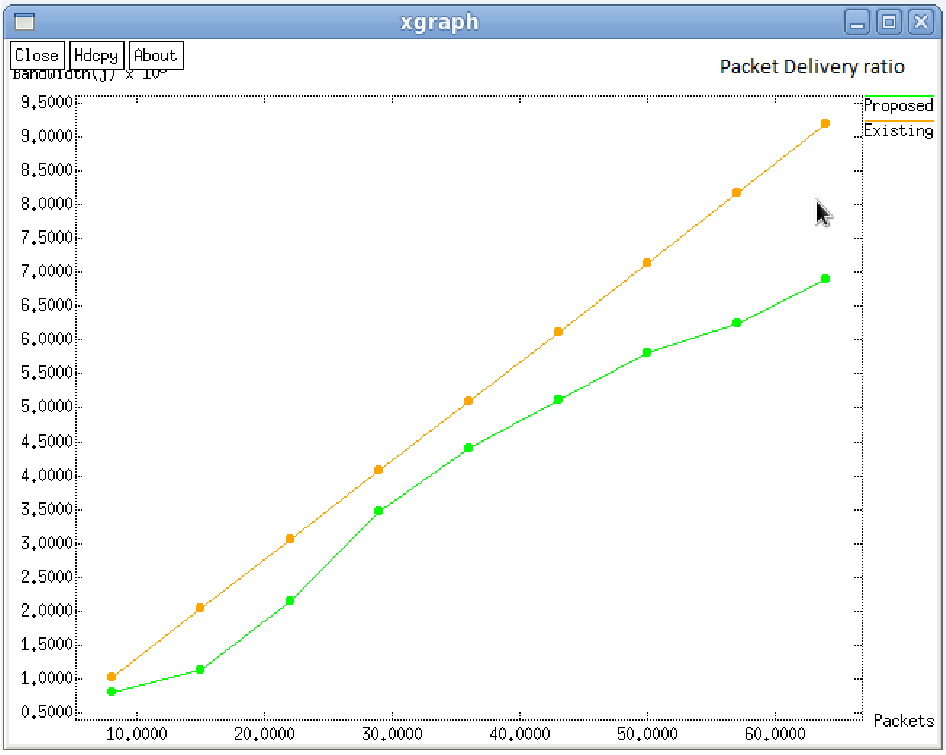

Figure 5: Performance Analysis of Proposed Framework against Existing Technique through Packet Delivery Ratio

The Figure 5 demonstrates the performance of the packet delivery ratio on multiple mobile sink scheduling on WBAN. In proposed framework, critical WBANs are efficiently mapped to the H-CSP, therefore the WBANs can send their data immediately. The proposed algorithm deals with the increase in traffic load and provides QoS to each WBAN. As a result, our proposed approach provides higher reliability than the existing schemes.

5. Conclusion

We designed and implemented a framework named as Ensemble learning based multiple mobile sink for energy efficiency of WBAN on health care data. Disease patient group formation optimizes the computational complexity of cluster formation. It employs heuristics, Boosting and bagging connection on the multiple mobile sink on data collection and transmission for sensor self-organization, adopts collaborative intercluster communication for energy-efficient transmissions. The proposed architecture has been modelled with different energy model to acquire the health information. Performance evaluation demonstrates the effectiveness of the proposed framework. The energy consumptions strategies and constraints of the proposed model alleviate the routing burdens on nodes towards balancing workload. Further mobile sink is scheduled according to high queue nodes to less data queues nodes. Evaluation is carried out on basis of varying network size, Sink Speed and energy factors. The Simulation results proves that proposed framework outperforms state of art technique in terms of throughput, energy utilization and packet delivery ratio.

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