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DESIGN AND MODELING OF RESOURCE-CONSTRAINED IOT BASED BODY AREA NETWORKS

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Abstract. Due to the recent advancement and development of sensing, wireless, and communication technologies, there has been a shift in attention towards Body Area Networks (BANs). One of the most important services of BAN is the remote monitoring of patients, enabling doctors to observe, diagnose, and prescribe the patients without being physically present. Various vital signs are being monitored by body sensing devices installed inside, on or off the body of patients, but most of these devices are constrained in terms of resources such as storage, processing, bandwidth, and energy due to their smaller size. This paper aims at highlighting the key findings related to BAN applications, constrained resources, and various resource management techniques. The paper also presents the design and modeling of a resource-constrained BAN system and discusses the various scenarios of BAN in the context of resource constraints. It further proposes an Advanced Edge Clustering (AEC) approach to manage the resources such as energy, storage, and processing of BAN devices while performing real-time data capture of critical health parameters and detection of abnormal patterns. The comparison of the AEC approach is done with the Stable Election Protocol (SEP) through simulations and empirical data analysis. The results show an improvement in energy, processing time and storage requirements for the processing of data on BAN devices in AEC as compared to SEP.

Key words: Internet of Things, Edge Computing, Body Area Networks, Body Sensors

AMS subject classifications. 68M11

1. Introduction. Internet of Things (IoT) is a network of self-configuring objects (devices) that exchange data by interacting with the environment [1]. The main aim of IoT is to form a network of day-to-day life objects and make them programmable using wireless and sensor technologies, and pervasive connectivity. The pervasiveness of IoT eases everyday activities such as data exchange by devices while sensing, reacting to events in the application environments; one of the most important sectors is the healthcare industry [2][3]. With the advance of wireless and sensor technologies, there has been more penetration of IoT devices in IoT enabled healthcare applications. The Body Area Networks is one of IoT enabled healthcare applications that employs body sensors inside, on or off the body of patients for remote monitoring of patients [4] [5]. In BAN applications, the patients are being monitored by using IoT based wireless sensors that sense and transmit the data to the Personal Digital Assistant device (edge) for further processing and storage. Various vital signs are being monitored by body sensors while offering flexibility to patients to move. The edge raises the alarms in case of any abnormality in the physiological data.

The world of BAN is broad and multifaceted and one may even find it complex due to the plethora of applications that it encompasses. From non-medical applications to medical applications of BAN, the world is all set to undergo a shift in IoT healthcare. According to recent reports in Gartner, there will be an increase in 19% BAN devices by 2021, out of which 42% will constitute medical IoT devices and rest will constitute the non-medical IoT devices. Several smaller sized IoT devices are used in BAN for patient monitoring e.g., EMG, ECG, EEG, Fingertip Pulse Oximeter, Inertial Measurement Unit, Blood Pressure, Accelerometer, Temperature sensors, Body Humidity, etc [6]. Due to the smaller size of these devices, most of these devices are constrained in terms of resources such as processing, energy, storage, and bandwidth [7]. In addition to this, the BAN devices in such systems cannot be controlled dynamically leading to the transmission of unnecessary readings which causes further wastage of resources especially energy, storage, processing, and bandwidth.

Due to the limited resources in BAN, there are open challenges at different levels of hardware design and software development, as such research is being carried out in finding resource-efficient algorithms and protocols

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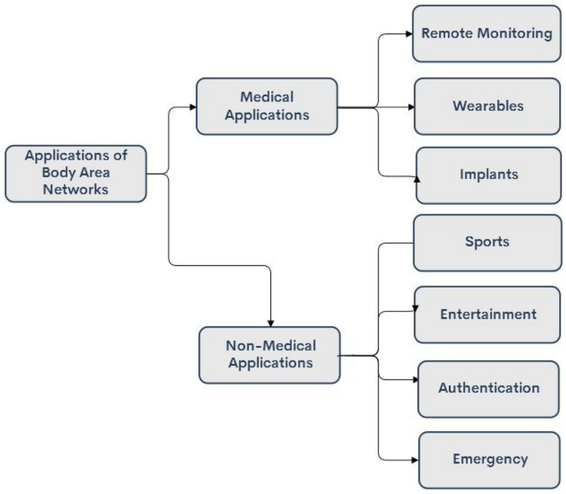

Fig. 2.1. *Applications of Body Area Networks*

that can store, process, and transfer the data with optimized resource management. There has been research in BAN resource management through data compression [8], data fusion [9], communication [10], network topology [11], machine learning techniques [12], and clustering approaches [13]. The main goal of all is to have seamless remote monitoring of patients by proper management of resources. However, none of the papers address resource constraints as a whole, which gives us the motivation to design, model, and implement a resource-efficient BAN system that could take into account more of the resource parameters.

This paper highlights the key findings related to BAN applications, constrained resources, and various resource management techniques. The paper also presents the design and modeling of a resource-constrained BAN system and discusses the various scenarios of BAN in the terms of resource constraints It further proposes an Advanced Edge Clustering approach for remote monitoring of patients with proper management of resources. In addition to this, an anomaly detection algorithm is also proposed that gives BAN the capability to detect false alarms. The comparison of the AEC approach is done with SEP [14], and the results are presented in the form of graphs and necessary explanation.

The organization of the paper is: Section 2 discusses literature survey, section 3 gives design and modeling of Body Area Networks, Section 4 discusses the evaluation of resource consumption in BAN scenarios, Section 5 presents proposed Advanced Edge Clustering approach, section 6 discusses simulation setup and evaluation and section 7 gives the conclusions.

2. Literature Survey. Over the last few years, there has been research on Body Area Networks highlighting the key findings related to applications, resources and constraints of BAN, and various techniques to address these constraints [15][16] [17], as discussed below.

2.1. Applications of BAN. From non-medical applications of BAN such as social networking, gaming, etc to medical applications of BAN such as body sensors for monitoring our health, the world is all set to undergo a shift in IoT healthcare. There are numerous applications of BAN which are categorized into medical and non-medical applications as shown in Figure 2.1.

2.1.1. Medical Applications. BAN has wide applicability in medical fields. Based on the devices used in medical applications, we have categorized BAN devices into remote monitoring devices, wearable devices, and implant devices as discussed below.

- Remote monitoring BAN devices allow us to keep track of patient's health parameters and provide real-time feedback to the patients at home [18]. The intent of remote monitoring by BAN devices is to provide affordable remote healthcare to people at home ,and avoid hectic interactions and travel

Table 2.1
Classification of studies carried out in BAN applications

Category	Ref.	Focus	Types	Constraints
Medical Applications	[18]	Monitoring heart rate, body temperature, respiration rate, etc	Remote Monitoring	Communication Interference
	[19]	Monitoring of heart rate	Remote Monitoring	Communication Interference
	[20]	Exercise monitoring	Remote Monitoring	Delay
	[21]	Temperature and blood pressure monitoring (ASNET)	Remote Monitoring	Security
	[22]	Monitoring activities of soldiers in battlefield	Wearable	Security, Privacy and authentication
	[23]	Monitoring health of Athlete	Wearable	Storage and Processing, Motion Interference
	[24]	Sleep monitoring	Wearable	Storage and Processing
	[26]	Monitoring cardio-vascular diseases and other abnormalities of physical	Health Implants	Environmental challenges
		Cancer detection and tumor diagnosis by sensors	Implants	Environmental challenges
Non-Medical Applications	[27]	Body movement and temperature of trainee	Sports	Environmental Inferences, Security
	[26]	Gaming by body gestures, hand movements, etc	Entertainment	Environmental Factors
	[33]	Biometric parameters (Fingerprint, hand geometry, retina recognition, etc)	Authentication	Environmental Factors
	[34]	Fire alarms, notification management	Emergency	Heterogeneity

to healthcare institutions and hospitals. In addition to this, remote monitoring of patients helps in the continuous assistance of the patient's health condition by timely sending of data to the doctors. Therefore, doctors find it easy to follow up patients either by video conferencing or phone calls. Considerable work in this includes real-time exercise monitoring [19], monitoring health parameters such as temperature and blood pressure [20][21], etc.

- Wearable BAN devices are normally attached to body surface using straps. Considerable work in this includes activity monitoring of soldiers at battlefield [22], monitoring of athletes [23], BAN based sleep monitoring [24], etc.
- Some BAN devices are implanted inside the body e.g., visual implants for recovering retinal degeneration problems of a patient [25], while others are used to monitor various abnormalities of physical health e.g., cardiovascular diseases, cancer monitoring [26], etc.

2.1.2. Non-Medical Applications. The applications of BAN are not confined to medical applications only but also used in various non-medical applications [27]. With the advance in BAN technology, it is widely used in many non-medical application areas such as sports, entertainment, emergency, and authentication as discussed below.

- BAN is mainly used in the field of sports for motion recognition and physiological status detection, which helps sportspersons with the correction of postures and improvement of skills. Considerable work in this includes heart rate measurement system [28], BAN based kinematic analysis of swimming strokes [29], etc .
- BAN is also used in entertainment such as social networking, gaming, get together with friends, making phone and video calls, etc [26].
- BAN finds its applicability for authentication purposes such as face detection [30], fingerprint [31], iris recognition [32], etc [33].
- BAN devices are useful in the detection of household smoke, fire, poisonous gases, etc [34]. It plays an important role to make workplace and homes safer to stay in.

Table 2.1 shows the classification of studies carried out to evaluate the applications of BAN.

2.2. BAN Resources and Constraints. The Body Area Network typically consists of a collection of low-power, miniaturized, lightweight devices with wireless communication capabilities that operate in the

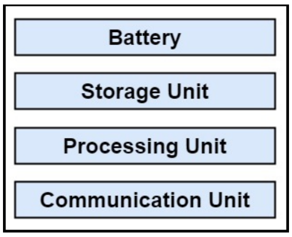

Fig. 2.2. *Resources in BAN Device*

proximity of a human body. An important aspect of these devices is its resources. As shown in Figure 2.2, a typical battery-operated BAN device possesses energy, storage, processing, and bandwidth as its resources [35]. Due to the smaller size of BAN devices, there are resource constraints in such applications. The resource constraints and related issues faced in Body Area Networks are discussed as [36]:

- Battery: Body sensing devices have limited energy which becomes one of the main constraints of BAN applications. Various solutions such as compression techniques sleep modes, low energy consumption hardware, etc are major design issues in BAN applications.
- Computation: Body sensing devices possess limited computing capabilities i.e., less processing power and storage which becomes challenging to store and process the data sensed by body sensors.
- Communication: BAN environments have limited communication and connectivity. As the number of body sensors increases, the number of transmissions increases which in turn demands more connectivity. Thus, limited communication and connectivity are major challenges in resource management.
- Security: In BAN applications, the transmitted data from the body sensors to the edge should be accessed only by authenticated entities. Any tampering in the information can cause serious issues such as a patient's death. As such, there is a need of securing this information, but implementing any security algorithm incurs resource overhead leading to more energy consumptions.
- Environmental Interference: There are many challenges faced by BAN applications due to environmental factors e.g., movement of the body can lead to a change in position of BAN devices, leading to path loss and incomplete reception of data in BAN applications, thus causing resource overheads.
- Heterogeneity: In BAN environments, there is heterogeneity in data types and measurements, leading to high complexity and resource overheads in such applications. Management of heterogeneity at the hardware and software levels is one of the major challenges in BAN applications.

2.3. Resource Management Techniques. Due to limited resources in BAN, there are open challenges at different levels of hardware design and software development, as such research is being carried out in finding resource-efficient algorithms and protocols that can store, process, and transfer the data as per application requirements and with optimized resource management. Most of the work has been carried out through data compression, data fusion, communication, network topology, machine learning techniques, and clustering approaches. The main goal of all is to have seamless remote monitoring of patients by proper management of resources.

2.3.1. Compression. BAN devices are mostly constrained in terms of energy, storage, processing, and communication. There have been recent studies in compression techniques that aim to reduce energy consumptions on BAN devices by reducing the data size to be transmitted from BAN devices to the sink (edge node) instead of transmitting to the sink directly. Considerable work in this include compression algorithm that aims to reduce the number of data transmissions and enhances real-time experience [37], Joint orthogonal matching pursuit that aims to reduce the number of transmissions, and storage and processing of data [8], compressive sensing that aim to reduce data rate [38], DFT method that aims to compress data [39], etc. There has been work on compression techniques in ECG monitoring as well and these include a compression algorithm based on WT that aims to reduce frame size and low delay [40], Quadratic compression algorithm that aims to reduce energy consumptions [41], etc.

Limitation: Most of the work in compression techniques focuses on optimizing energy utilization. No attention is paid towards other resources such as storage, processing, and bandwidth.

2.3.2. Data Fusion. In Body Area Networks, the body sensors sense several physiological data about the patient or elderly, and while sending the data from the sensors to edge, BAN face many challenges at the node and network levels. Data manipulation is one of the main challenges faced in BAN and to address this, various data fusion mechanisms are employed that combine data from multiple body sensors into more accurate information than an individual body sensor [42]. Considerable work in this includes data fusion techniques that achieve effective noise filtering and accurate inferences [9], data fusion mechanisms to reduce energy consumptions, minimize data redundancy and increase network lifetime [43], etc.

Limitation: Most of the work in data fusion techniques focuses on optimizing energy usage and little attention is paid towards storage, processing, and bandwidth as a resource.

2.3.3. Network Communication. In BAN applications, a typical node is characterized as a non-rechargeable and resource-constrained device. Due to the limited transmission range of these devices, an Edge-IoT network is formed wherein edge nodes are deployed hierarchically to process the real-time data in such applications. In many BAN applications such as implants, body sensors are deployed inside the human body, as such the electricity of the body affects the communications, that take place among the sensors or from sensors to edge. There is research going on sensor and communication technologies to address these issues such as radio technologies and other communication protocols in BAN applications [44], data communication to enhance Quality of Service and security [10], adaptive multi-hop routing protocol to improve network lifetime for multi-hop wireless body area network [45], medical implant communications service suitable for low data rate networks [46], etc.

Limitation: Most of the work in this focus on optimizing bandwidth,energy utilization and security. Little attention is paid towards storage and processing.

2.3.4. Topology. Deployment of BAN sensors is possible in several different topologies; the simplest topology is the single-hop star where every node communicates its sensed data to the sink node directly. The most commonly used topology in BAN is star topology [47][48]. This topology simplifies the network design but the disadvantage is that it is less robust and scalable. For larger networks, multi-hop routing is necessary, which depends on the placement or arrangement of body sensors in a network. The multi-hop routing drains less energy than direct routing but it increases the network delay, therefore, direct communication is better in scenarios where nodes are closer to edge nodes. Currently, research is going on multi-hop networks, most of the research focuses on energy acquisition, human body channels, etc to give better BAN services [11]. In BAN applications, the nodes can be deployed in a structured or randomized manner depending on the application requirement [49]. In structured deployment, nodes are placed at a fixed spot and routing paths are predetermined. In randomized deployment, nodes are scattered randomly. In most of the BAN applications, nodes are mobile which a major challenge in such environments becomes. An efficient node deployment scheme is needed to reduce the complexity caused due to mobility. Further, there are challenges in node deployment such as redundant data, energy consumption, delay, storage, coverage, etc that need to be taken care of in such applications.

Limitation: Most of the work in this focuses on optimizing energy utilization and delay. Little attention is paid towards other resources.

2.3.5. Machine Learning. Machine learning techniques are foreseen to transform healthcare by completing tasks with lesser delay and greater accuracy by using few resources of BAN devices. Machine learning techniques such as genetic algorithm [50], fuzzy logic [51], KNN [52], SVM [53], decision tree[54], neural network [55], etc are used for feature extraction and building decision models for prediction. The data analysis and prediction, done by machine learning algorithms, helps to make data-driven decisions, predict outcomes, and detect anomalies, which are useful for end-users. Considerable work in this includes leg motion classification with artificial neural networks [56] [57], human activity recognition system based on acceleration and vital sign data [58], real-time continuous glucose monitoring [59], etc.

Limitation: Most of the work in machine learning techniques focuses on optimizing delay. Little attention is paid towards optimizing resources.

Table 2.2
Summary of literature survey

Summary	Related Work	Benefits
Compression	Compression Algorithm [37]	Reduced Number of data transmissions
	Joint Orthogonal Matching Pursuit [8]	Reduced Number of data transmissions, Improved Storage and Processing of data
	Compressive Sensing [38]	Reduce Data Rate
	WT Compression Algorithm [39]	Reduce Frame Size Low Delay
	Quadratic Compression Algorithm [40]	Low Energy Consumptions
Data Fusion	Data Fusion in BAN [9]	Effective Noise Filtering, Accurate Inferences
	Data Fusion Mechanisms [43]	Reduced Energy Consumptions, Increased Network Lifetime, Low Data Redundancy
Network Communication	Data communication [45]	Enhanced Quality of Service Security
	Medical Implant Service [46]	Low data rate networks
Topology	Star BAN [47][48]	Less delay
	Multi-hop BAN [11]	Low energy consumption
Machine Learning	Leg motion classification with artificial neural networks [56]	Less delay
	Human activity recognition based on acceleration and vital sign data [58]	Less delay, Better Accuracy
Clustering	LEACH [61], SEP[14], etc	Improves energy utilization

2.3.6. Clustering Approaches. Clustering approaches are considered as one of the effective mechanisms to manage resources in resource-constrained IoT applications. In clustering, the IoT network is divided into clusters with each having a cluster head (CH) to reduce the consumption of resources. Considerable work in this includes data aggregation guaranteeing low communication and storage costs in IoT [60], a cross-layer data aggregation scheme increasing energy efficiency [13], etc. There has been a lot of work in clustering on data aggregation protocols for Body Area Networks such as Low-Energy Adaptive Clustering Hierarchy (LEACH) [61], Anybody [62], SEP [14], etc. LEACH is the simple clustering protocol in which nodes elect cluster Head based on a pre-defined probability while the other nodes join the closest cluster head [61]. Another data gathering protocol is 'Anybody' that uses clustering to reduce the number of direct transmissions to remote base stations [62]. There has been a lot of work in BAN resource management via SEP [14]. In SEP, a fraction 'm' advanced nodes in a total of 'n' nodes are provided with an additional energy factor, thereby increasing the stability period due to advanced nodes. The disadvantage is since advanced nodes become more frequently CHs, the energy of advanced nodes becomes less than the normal nodes. To overcome this, many modified versions of SEP have been introduced to achieve resource savings than the traditional one to some extent [63][64].

Limitation: There has been work in clustering approaches in IoT but most of the work focuses on energy. No attention has been paid towards other resources.

Table 2.2 gives the summary of above discussed research papers in terms of benefits that the BAN applications get. And Table 2.3 gives the summary of above discussed papers in terms of resource parameters that these papers have addressed. It is evident that none of the papers have focused on addressing resource constraints as a whole and therefore, it gives us the motivation to design, model, and implement a resource-efficient BAN system that could take into account more of the resource parameters.

3. Design and Modeling of Body Area Networks. Consider a BAN system where a patient or elderly wears IoT based body sensing nodes (devices), that sense medical parameters such as temperature, blood pressure, sugar level, etc to a central edge that integrates patient's medical data. It then transfers the data to the cloud or backend servers for related diagnosis. Figure 3.1 shows a general BAN system consisting of three levels viz. sensor level, edge level, and the cloud level.

At the bottom level, there are many sensors such as ECG, EEG, EMG, breathing sensor, etc that measure the physiological parameters of a patient or elderly at home. These sensors generate data combined on the Personal Assistance Device (edge level) to generate information. The information on these devices is pushed on the third level i.e. cloud for further processing and analysis to generate more information. For example, the medical data of patients on the edge devices can be merged to create a community of patients giving more

TABLE 2.3
Summary of literature survey in terms of Resource Parameters

Ref.	**Number of Transmissions**	**Storage**	**Processing**	**Delay**	**Energy**	**Quality of Services**	**Security**
[37]	✓						
[8]	✓	✓	✓				
[38]	✓						
[39]	✓			✓			
[40]					✓		
[9]						✓	
[43]					✓		
[45]						✓	✓
[46]	✓						
[47]							
[48]				✓			
[11]					✓		
[57]				✓			
[58]				✓			
[61]					✓		
[14]					✓		

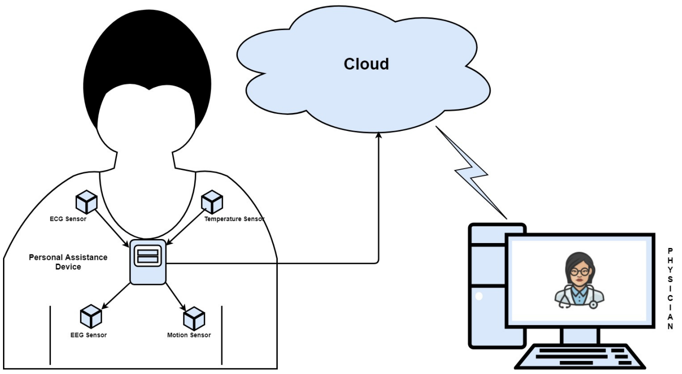

FIG. 3.1. *A General BAN System*

information about the patient's status in the entire city.

3.1. BAN Entities. In this section, we discuss the basic BAN entities such as body sensing nodes, edge and cluster.

3.1.1. Body sensing Node. A BAN network consists body sensing nodes, defined as a four tuples, $B_i = \{B_{id}, B_{st}, d_i, R_i\}$, where

- B_{id} represents the unique ID of body sensing node, B_i,
- B_{st} represents the status of body sensing node, B_i,
- d_i indicates the data items that a node senses,
- B_{Ri} represents the resource status of a body sensing node, B_i.

3.1.2. Edge. An edge node, E_i in BAN application is defined as two tuples, $E_j = \{E_{id}, R(E_j)\}$, where,

- E_{id} is the ID of edge, and
- $R(E_j)$ gives the resource status of the edge.

3.1.3. Cluster Formation. A cluster, C_i corresponds to a logical boundary comprising of several localized body sensing nodes, represented as three tuples, $C_i = \{C_{id}, B[U], E_{id}\}$, where,

- C_{id} is the ID of the cluster,
- $B[U]$ is the non-empty ID array of size U that stores IDs of all corresponding body sensing nodes,
- U is a dynamic value that is decided by the number of body sensing nodes present in a particular cluster, and
- E_{id} is the ID of the edge.

3.2. Data Model. The body sensing nodes,B_i are dedicated to monitor a patient (P_1), which transfers the data to the edge (E_j). To ensure secure communication in BAN applications, the body sensing nodes and personal edge will have unique IDs D_{idn} and E_{id} respectively. The state of body sensing node is denoted by a Boolean $B_{st} = \{0, 1\}$, where the values 0 and 1 symbolize the inactive and active states respectively. When the state of body sensing node is active, it will be able to sense and monitor the health parameters about a patient in the form of data items. These data items together constitute the patient's medical data.

At body sensor level, we have:

$$B_i \rightarrow d_i \quad Where 1 <= i <= n \tag{3.1}$$

At BAN level, we have:

$$\{B_1, B_2, B_3, ..., B_n\} \rightarrow \{d_1, d_2, d_3, ..., d_n\} \tag{3.2}$$

3.3. Resource Model. In BAN, a workload encompasses resources such as storage, processing, energy and network bandwidth requirements. It becomes essential to monitor the resources for their better allocation to accommodate this application workload. For each body sensing device B_i, the resources are denoted as:

$$R_i = \{E_i, P_{ri}, S_i, B_{wi}\} \tag{3.3}$$

where E_i represents energy, B_{wi} represents bandwidth,S_i represents storage, and P_{ri} represents processing of a body sensing node.

If $\{R_1, R_2, R_3, ..., R_n\}$ denotes the status of monitored resources of body sensing nodes $(B_1, B_2, B_3, ..., B_n)$ such as energy $(E_1, E_2, E_3, ..., E_n)$, bandwidth $(B_{w1}, B_{w2}, B_{w3}, ..., B_{wn})$, processing$(P_{r1}, P_{r2}, P_{r3}, ..., P_{rn})$ and storage $(S_1, S_2, S_3, ..., S_n)$ respectively. Then at the system level, the resources can be represented as:

Total energy, E_{P1} is given as:

$$E_{P1} = \sum_{i=1}^{n} E_i \tag{3.4}$$

Total processing power, P_P1 is given as:

$$P_{P1} = \sum_{i=1}^{n} P_{ri} \tag{3.5}$$

Total bandwidth, B_{P1} is given as:

$$B_{P1} = \sum_{i=1}^{n} B_{wi} \tag{3.6}$$

Total storage, S_{P1} is given as:

$$S_{P1} = \sum_{i=1}^{n} S_i \tag{3.7}$$

The total resources (R_{P1}) of BAN is given as:

$$R_{P1} = \{E_{P1}, E_{P1}, B_{P1}, S_{P1}\} \tag{3.8}$$

3.4. Allocation Model. At node level, the value of each resource is given as:

$$E_i = W_i; P_{ri} = X_i; S_i = Y_i; B_{wi} = Z_i; \tag{3.9}$$

where W_i, X_i, Y_i, Z_i denotes the maximum value for energy, processing, storage and bandwidth respectively. Once the workload is accommodated by proper allocation of resources, the value of resources becomes:

$$\begin{aligned} E_i &= W_i - w_i; \\ P_{ri} &= X_i - x_i; \\ S_i &= Y_i - y_i; \\ B_{wi} &= Z_i - z_i; \end{aligned} \tag{3.10}$$

where w_i, x_i, y_i, z_i denotes the consumed values for energy, processing, storage and bandwidth respectively. Considering the constraints of BAN, the resource allocation can be taken as an optimization problem that maximizes the resource availability. Therefore, at the node level, we have:

$$\text{Maximize } E_i P_{ri} S_i B_{wi} \tag{3.11}$$

Subject to constraints

$$\begin{aligned} E_i &<= W_i; \\ P_{ri} &<= X_i; \\ S_i &<= Y_i; \\ B_{wi} &<= Z_i \end{aligned} \tag{3.12}$$

The above BAN model can be extended to community level which can result in the creation of BAN grids, favorable in smart city IoT applications.

4. Evaluation of resource consumption in BAN Scenarios. The possible scenarios which arise in BAN applications, depending on whether the BAN entities are stationary or mobile, include stationary body sensing nodes and edge, stationary body sensing nodes and mobile edge, mobile body sensing nodes and stationary edge, and body sensing nodes and edge.

4.1. Stationary body sensing nodes and edge. In BAN applications with stationary body sensing and edge nodes, the location of all nodes is pre-determined. Let $\{B_{11}, B_{12}, \ , B_{1i}, B_{21}, B_{22}, , B_{2j}, , B_{n1}, B_{n2}, , B_{nk}\}$ be the set of stationary body sensing nodes and $E_1, E_2, ..., E_j$ be the set of stationary edge nodes such that a fixed number of body sensing nodes are associated to a particular edge node in each cluster i.e;

$$\begin{aligned} \{B_{11}, B_{12}, ..., B_{1i}\} &\in E_1, \\ \{B_{21}, B_{22}, ..., B_{2j}\} &\in E_2, \\ &..., \\ \{B_{n1}, B_{n2}, ..., B_{nk}\} &\in E_j \end{aligned} \tag{4.1}$$

Let $\{(x_{11}, y_{11}), (x_{12}, y_{12}), (x_{13}, y_{13}), ..., (x_{1i}, y_{1i}), (x_{21}, y_{21}), (x_{22}, y_{22}), (x_{23}, y_{23}), ..., \ (x_{2j} \ , y_{2j}), , (x_{1i}, y_{1i}), ... (x_{n1}, y_{n1}), (x_{n2}, y_{n2}), (x_{n3}, y_{n3}), ..., (x_{nK}, y_{nK})\}$ denotes the positions of body sensing nodes $\{B_{11}, B_{12}..., B_{1i}, B_{21}, B_{22}, ..., B_{2j}, ..., B_{n1}, B_{n2}..., B_{nk}\}$ respectively and $\{(x_{e1}, y_{e1}), (x_{e2}, y_{e2}), (x_{e3}, y_{e3}), ..., (x_{em}, y_{em})\}$ denotes the positions of edge nodes $\{E_1, E_2, ..., E_m\}$ respectively. For a particular cluster, say C_1, the distance between the body sensing nodes, B_{11} and B_{12} is calculated as:

$$d_{11} = \sqrt{(x_{11} - x_{12})^2 + (y_{11} - y_{12})^2} \tag{4.2}$$

The distance between the body sensing nodes, B_{11} and edge node, E_1 is calculated as:

$$D_{11} = \sqrt{(x_{11} - x_{e1})^2 + (y_{11} - y_{e1})^2} \tag{4.3}$$

Since all the nodes are stationary, the distance between the nodes is definite. At the time of deployment, the size of cluster is stationary i.e., known number of body sensing nodes is associated with a particular edge. The body sensing nodes sense and generate data items $\{d_{i1}, d_{i2}, ..., d_{in}\}$ which is aggregated on the edge, E_j, forming a cluster, which is later pushed to the cloud.

For each cluster, C_i we have $\{R(B_{i1}), R(B_{i2}), R(B_{i3}), ..., R(B_{in})\}$ that denotes the status of resources such as energy $\{E_{ei1}, E_{ei2}, E_{ei3}, ..., E_{ein}\}$, bandwidth $\{B_{wi1}, B_{wi2}, B_{wi3}, ... , B_{win}\}$, processing $\{P_{i1}, P_{i2}, P_{i3}, ..., P_{in}\}$ and storage $\{S_{i1}, S_{i2}, S_{i3}, ..., S_{in}\}$ for body sensing nodes $\{B_{i1}, B_{i2}, B_{i3}, ..., B_{in}\}$ respectively. And in each cluster, C_i the resources of edge node, $R(E_j)$ is always higher than that of body sensing nodes $\{R(B_{i1}), R(B_{i2}), R(B_{i3}), \ldots, R(B_{in})\}$, i.e.

$$R(E_j) >> R(B_{i1}) \text{ or } R(B_{i2}) \text{ or } R(B_{i3}) \text{ or } \ldots \text{ or } R(B_{in}) \tag{4.4}$$

Also, the resources of edge node are sufficient for associated body sensing nodes, i.e;

$$R(E_j) = R(B_{i1}) + R(B_{i2}) + R(B_{i3}) + \cdots + R(B_{in}) \tag{4.5}$$

Considering the resource constraints at the node level, the resource allocation model manages these resources in an optimized way. In each cluster, the edge will monitor the resources of body sensing nodes in such a way that it maximizes the availability of energy, processing power, memory, and bandwidth. Resource consumption occurs mainly due to the processing and transmission of data as per the application requirements. Such BAN applications are less resource-constrained because there is only one-time processing involved in calculating parameters such as the position of nodes, the distance of nodes, etc.

4.2. Stationary body sensing nodes and mobile edge. In BAN applications with stationary body sensing nodes and mobile edge nodes, only body sensing nodes have fixed positions. In such scenario, a fixed number of body sensing nodes are associated to any edge at a particular instance of time is given as:

$$\begin{aligned} B_{11}, ..., B_{1i} &\in E_1 \text{ or } E_2 \text{ or } \ldots \text{ or } E_m \\ B_{21} ..., B_{2j} &\in E_1 \text{ or } E_2 \text{ or } \ldots \text{ or } E_m \\ &..., \\ B_{n1}, ..., B_{nk} &\in E_1 \text{ or } E_2 \text{ or } \ldots \text{ or } E_j \end{aligned} \tag{4.6}$$

Initially, an edge has a fixed location and a fixed number of body sensing nodes are associated with an edge node in a cluster. However, when edge nodes change their locations, the same fixed-sized cluster of body sensing nodes are now assigned to a new edge node depending upon the nearness of distance between an edge node and cluster of body sensing nodes i.e., the edge node closest to the body sensing node will act as the sink for the sensed data. Also in a particular cluster, the distance among the body sensing nodes is always fixed but the distance between the body sensing nodes and edge node needs to be re-calculated every time a new edge node becomes a sink of these body sensing nodes. In each cluster, C_i, body sensing nodes sense and generate data items that create mini-profiles of body sensing node on a neighboring edge. These mini-profiles are aggregated to form a profile, which then can be pushed to the cloud for further storage and analysis. The resource allocation model optimizes the use of resources in such BAN networks. Resource consumption occurs at a higher rate as compared to the above scenario because there are frequent calculations involved in determining the position and distance of mobile edge nodes.

4.3. Mobile body sensing nodes and stationary edge. In BAN applications with mobile body sensing nodes and stationary edge nodes, the resource consumption occurs at a higher rate as compared to above scenarios. This is because of the mobile behavior of body sensing nodes that drains the resources more quickly.

In such scenarios where there are mobile body sensing nodes but stationary edge, the association of body sensing node to the edge nodes is denoted as:

$$
\begin{aligned}
\{B_{11}, ..., B_{1i}, B_{21}, ..., B_{2j} \text{ or } ..., B_{n1}, ..., B_{nk}\} \in E_1, \\
\{B_{11}, ..., B_{1i}, ..., B_{21}, ..., B_{2j} \text{ or } ...., B_{n1}, ..., B_{nk}\} \in E_2, \\
..., \\
\{B_{11}, ..., B_{1i}, ..., B_{21}, , B_{2j} \text{ or } ...., B_{n1}, , B_{nk}\} \in E_j
\end{aligned}
\tag{4.7}
$$

i.e., mobile body sensing nodes can be assigned to a particular edge. For each cluster, C_i, the distance between sensors and edge will vary and the distance among body sensing nodes will also vary. Initially, a known number of body sensing nodes are associated with a stationary edge node. But as the body sensing nodes change their locations, any random set of body sensing nodes are assigned to an edge node depending upon the nearness of distance between an edge node and body sensing nodes. The size of the cluster is not predefined and each cluster can either shrink or expand depending on the movement of body sensing nodes. For example, initially $C_1 = \{B_{11}, B_{12}, B_{15}\}$ and $C_2 = \{B_{21}, B_{25}, B_{35}\}$, after few round, $C_1 = B_{11}, B_{12}$ and $C_2 = \{B_{15}, B_{21}, B_{25}, B_{35}\}$.

In such BAN applications where body sensing nodes are moving and edge nodes are stationary, the resource consumption occurs at a higher rate compared to the above two scenarios. Considering such resource constraints at the node level, the resource allocation model manages resources in an optimized way.

4.4. Mobile body sensing nodes and edge. In applications having mobile nodes, the association of body sensing node to the edge nodes is denoted as:

$$
B_{11} \text{ or } ... \text{ or } B_{1i} \text{ or } B_{21} \text{ or } ... \text{ or } B_{2j} \text{ or } ... \text{ or } B_{n1} \text{ or } B_{n2} \text{ or } ... \text{ or } B_{nk} \in E_1 \text{ or } E_2 \text{ or } ... \text{ or } E_j \tag{4.8}
$$

i.e., any body sensing node can be assigned to any edge node depending upon the nearness of distance between the body sensing node and an edge node. Since nodes are randomly moving, temporary clusters are formed. For each temporary cluster, C_i, the distance between the body sensing node and edge node, and the among the body sensing nodes vary. In these applications, the resource consumption is highest. Thus, it is necessary to monitor these resources for efficient resource allocation that leads to better management of resources in such a way that it maximizes the availability of energy, processing, memory, and bandwidth on body sensing nodes. In this scenario, resource consumption is highest due to the high randomness of nodes.

5. Proposed Advanced Edge Clustering. In the proposed Advanced Edge Clustering approach, an advanced edge is employed that takes into account not only energy but storage and processing as well. The properties of the advanced edge are as under:

- The energy of the edge node is higher than the body sensing nodes such that it lasts till the last node dies,
- The processing power and storage of the edge is higher than the body sensing nodes,
- The distance of the body sensing nodes from the edge is lesser as compared to the distance from edge to the cloud,

In AEC, an advanced edge node, which is a pre-defined node, is used for each cluster. This superior node has higher resources such as processing, energy, and storage than body sensing nodes (as shown in eq. 4.4) and in each cluster, an edge node has sufficient resources to accommodate the workload of sensing nodes (as shown in eq. 4.5). The sensed data is collected by the edge nodes. And as the size of sensed data increases, resources of the edge node become insufficient and therefore data is pushed to the cloud for storage and processing as and when needed.

If the number of BAN applications increases in number, more edge nodes offload their computation to the cloud if physical edge nodes are not sufficient to accommodate the workload incurred by such applications and in that case, we have:

$$
\{E_1, E_2, E_3, , E_k\} \rightarrow C_L \tag{5.1}
$$

Table 6.1
Simulation Parameters

Parameters	Value
Setup Area (Network Size)	500 * 500 m^2
Number of Body Sensing Nodes for each Patient	4
Number of Edge	1
Initial Energy of Body Sensing Node	200 Joules
Initial Energy of Edge	1000 Joules
Storage of Body Sensing Node	30KB
Storage of Edge	1.5MB
Distance between Body Sensing Node and Edge	10m
Packet Size	512bytes

Besides monitoring the health parameters, the AEC approach uses an anomaly detection algorithm that raises alarm for the emergency team when any abnormal pattern is detected. It seeks to detect abnormal values to reduce false alarms resulting from faulty measurements while differentiating faults from patient health degradation (see Algorithm 1).

Algorithm 1 Proposed Algorithm

For each received record x do
Classify x using svm
If Class(x) == "ABNORMAL" then
Find out number of violations (V)
If V > 1: then
Call emergency procedure
else
Predict using regression
If error < threshold: then
Call emergency procedure
else
Declare false alarm

If the difference between the current value and the estimated value is larger than the pre-defined threshold for only one attribute, the measurement is considered faulty and is considered as a false alarm. However, if the readings are higher than the threshold, a medical alarm is triggered for the emergency team to react.

6. Simulation set-up and Evaluation. The simulation results are based on the proposed Advanced Edge Clustering approach as discussed in section 5. The simulation parameters are listed in Table 6.1.

The proposed approach has been tested on the Arduino board with body sensors (such as temperature sensor, breathing rate, heart rate sensor, blood pressure sensors, and movement sensor). To facilitate easy access to the microcontrollers, an Arduino integrated development environment is used and for the programming of microcontrollers, Python is used. We have also tested the proposed approach on dataset taken from the Physionet database consisting of three attributes viz., ABPsys, ABPdias, and HR to detect any anomaly in critical health parameters. The variations in physiological parameters are easily traced by the proposed anomaly detection algorithm.

The data has been captured over a period of time using the above setup and we have evaluated the proposed approach on this data as well. Since the proposed BAN system forms a heterogenous environment, therefore, the comparison of our proposed system is done with SEP [14], which is a standard protocol meant for a heterogeneous environment. The performance parameters used to evaluate the resource efficiency of the AEC approach include energy, processing time, and storage.

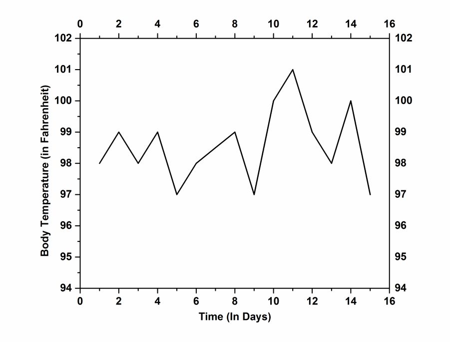

FIG. 6.1. *Body Temperature*

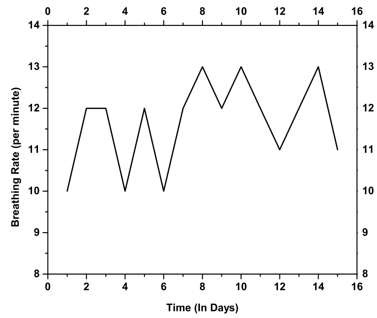

FIG. 6.2. *Breathing Rate*

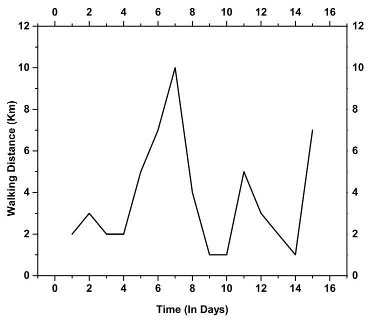

FIG. 6.3. *Walking Distance*

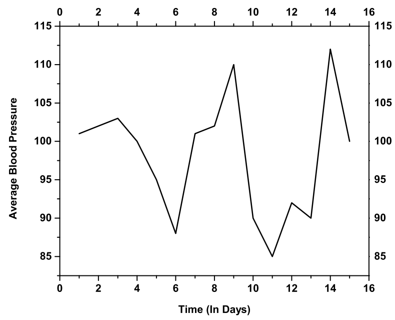

FIG. 6.4. *Average Blood Pressure*

6.1. Data Analysis. In this section, the real-time data capture and analysis is carried out in BAN. The sensed and gathered data from the IoT body sensing nodes were analyzed in the form of graphs. The Figure 6.1, 6.2, 6.3 and 6.4, which is indicative of body temperature, breathing rate, walking distance and blood pressure, gives an indirect method of prediction of diseases in patients.

6.2. Anomaly Detection. The proposed anomaly detection algorithm monitors the critical parameters for the detection of abnormality in a patient. Figure 6.5 shows the variations of heart rate for the monitored patients. The normal values for heart rate are in the range of [60-100] for a healthy human being. Any variation beyond this limit represents the abnormality.

Figure 6.6 shows the variations of blood pressure for the monitored patients and it is observed the blood pressure vary from one individual to another.

Figure 6.7 represents the correlation between monitored health parameters. The proposed anomaly detection algorithm triggers a medical alarm whenever any abnormality is detected in these measurements, otherwise the measurement is considered to be faulty and is discarded without raising any alarm.

6.3. Resource Analysis. The smaller size of BAN devices puts more constraints on resources such as storage, energy, and processing. It is evident from Figure 6.8, 6.9 and 6.10 that the resources of the device are more constrained as the size decrease.

In simulations, a round is the total time required in performing one complete operation of sensing, aggregation, and offloading from body sensing nodes to the edge node. While carrying out the simulations, the proposed AEC operates for a longer time as compared to SEP as shown in Figure 6.11.

Figure 6.12 depicts the storage versus the number of body sensing nodes in AEC and SEP. As the number of body sensing nodes in a cluster increases, the amount of sensed data also increases, and as such it requires sufficient space on the edge node. But as the size of data goes beyond the edge's capacity, the offloading of data from the edge to the cloud for storage becomes necessary. It is evident in AEC, the storage capacity of the edge is more than that of the cluster head in SEP, resulting in less number of offloads.

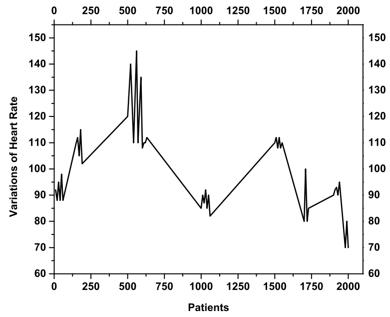

FIG. 6.5. *Variations of Heart Rate*

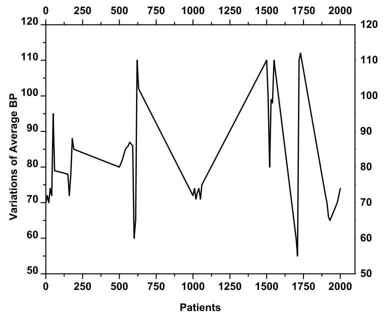

FIG. 6.6. *Variations of mean Blood Pressure*

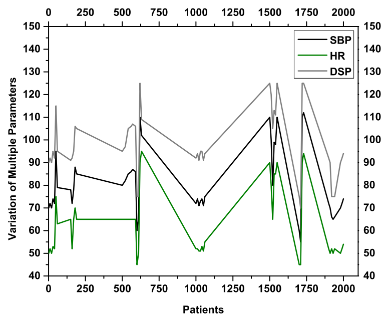

FIG. 6.7. *Variation of Multiple Parameters*

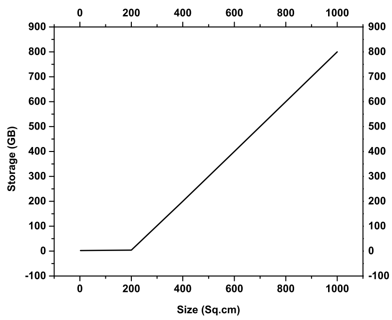

FIG. 6.8. *Storage in IoT Device*

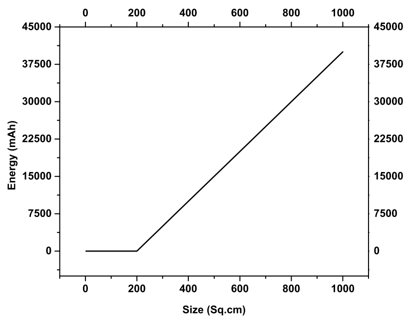

FIG. 6.9. *Energy in IoT Devices*

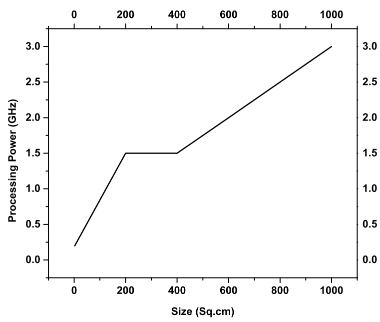

FIG. 6.10. *Processing in IoT Devices*

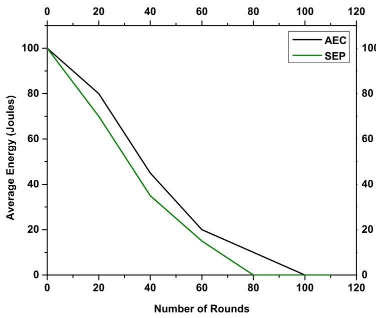

Fig. 6.11. *Energy versus Number of Rounds*

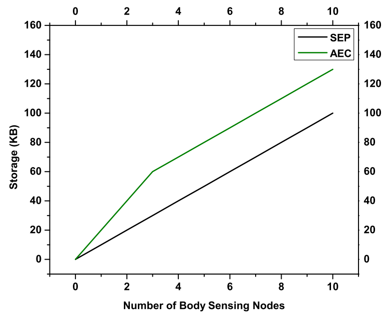

Fig. 6.12. *Storage versus Number of Body Sensing Nodes*

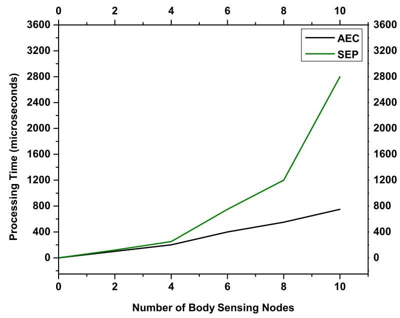

Fig. 6.13. *Processing Time versus Number of Body Sensing Nodes*

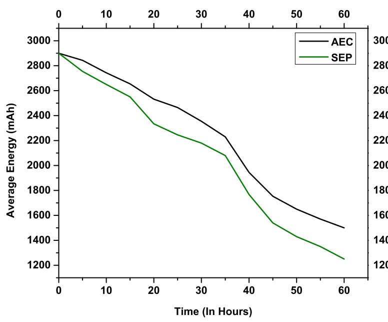

Fig. 6.14. *Energy versus Time*

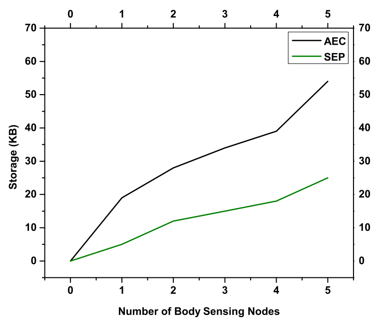

Fig. 6.15. *Storage versus Number of Body Sensing Nodes*

Figure 6.13 depicts the processing time versus the number of body sensing nodes in AEC and SEP. The processing time is more in SEP as compared to AEC because, in SEP, the edge node gets easily overloaded because of the limited processing capability of sensing nodes which results in more processing time.

The proposed AEC approach is also evaluated using empirical data to justify how the proposed approach suits the real-life scenario of BAN. Figure 6.14, 6.15 and 6.16 shows the energy versus time, storage versus the number of body sensing nodes, and processing time versus the number of body sensing nodes in AEC and SEP respectively. It is evident from these graphs that the energy, storage, and processing time are improved in AEC as compared to SEP in this case as well.

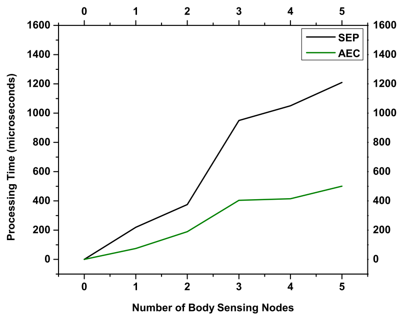

Fig. 6.16. *Processing Time versus Number of Body Sensing Nodes*

7. Conclusions. Body Area Networks is a newly emerging technology in the field of healthcare providing vital care and access not only to patients but to elderly and infants. It allows continuous, autonomous monitoring of patients and keeps the doctor informed of any abnormal fluctuations in the patient's health parameters by sending alarms and emergency services. The remote monitoring allows doctors to serve patients from any location where network connectivity exists.

Although BANs have been a hotspot of research with the emergence of wide range applications, there are open challenges in these. One of the most important challenges is the resource-constrained nature of BAN devices. Several small sized sensor-based wireless devices are used in BAN, the size of which is smaller as compared to other IoT applications. The smaller size of these devices puts more constraint on the use of resources such as energy, processing, bandwidth, and storage. This paper presented the design and modeling of these resource-constrained BAN systems along with its scenarios.

To address the resource limitations in BAN, we proposed an AEC approach that manages energy, storage, and processing time while monitoring the health parameters in patients. The comparison of the AEC approach is done with SEP and the simulation results showed an improvement in energy, processing time, and storage of AEC as compared to SEP. The comparative analysis is carried out on empirical data as well and it also showed an improved resources in AEC as compared to SEP, making the proposed solution suitable to meet the real-life scenarios of BAN.

The future research in BAN will be more interesting because of the pandemic situations like COVID-19 where it will be useful for doctors and paramedics to remotely monitor the patients as a safeguard measure.

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