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Energy-Aware Multisensor Adaptive Sampling and Assessment for Patient Monitoring based on IoHT

A Thesis

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By

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بسم الله الرحمن الرحيم

وَلَا يُحِيطُونَ بِشَيْءٍ مِنْ عِلْمِهِ إِلَّا بِمَا شَاءَ

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سورة البقرة (255)

Supervisors Certification

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Abstract

The rapid development in the Internet of Things (IoT) led to increasing advancement in the healthcare industry. The development in the hardware platform, as well as the underlying software, led to the emerging Internet of Healthcare Things (IoHT). The demand for remote healthcare continuous monitoring systems using limited resources biosensors is increased. These biosensors would increase the collected and transmitted data across the IoHT network. Therefore, decreasing the gathered data and make a decision at the Edge gateway can save the energy of biosensors and produce a quick response to the medical staff.

This thesis proposes an Energy-Aware Multisensor Adaptive Sampling and Assessment for Patient Monitoring in Connected Healthcare Applications. It is implemented on two levels in the Edge-based IoHT network: biosensors and the Edge gateway. In the biosensors, to remove redundant data during monitoring the status of the patients. It operates in the way of rounds. There are two periods in the round. The emergency discovery and adapting the sampling rate of each biosensor are two main steps in this level. The machine learning-based Support Vector Machine (SVM) is implemented at the gateway level. The SVM model is trained based on the collected data from the multisensors deployed on the body of the patient. This trained model can take a suitable decision about the status of the monitored patient.

In this work achieved several experiments based on real sensed data from the biosensors of the patients. The results explain that the proposed approach decreases the sent data from 93.5% up to 99% and saves 78.35% of energy in comparison with Carol's method. It keeps a good representation of the whole scores at the Edge gateway and provides accurate decisions according to the status of the patient.

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1.1. INTRODUCTION

Over the last years, an increasing amount of interest was focused upon the wireless body sensor networks (WBSNs) due to their vast, innovative, accurate and simultaneous applications of monitoring in various areas, which include healthcare, sport training and fitness, social interactions, and monitoring industrial workers. People are getting increasingly aware of the importance of health-care in their daily lives as the standard of living rises and the population ages. Wearable health monitoring (WHM) can be defined as a new technology which allows for continuous ambulatory monitoring of potions for recording the vital sign about their body and health without causing undue discomfort or interfering with their daily activities when they're at home, work, or other exercise-focused locations, or in a clinical setting[1]. The technical WHM device designs have been focused on four major areas: reliability and safety, low power consumption, ergonomics, and comfort [2].

The smart WHM systems can be provided in different forms skin-touch devices, implantable devices as well as another wearable tiny devices [3]and were used to monitor the vital signals regarding body and health body activity and location [4,5,6].On the other hand, the agreement level of (WHM) devices by end employer is low [7,8], in order to the data treatment technologies applied in the WHM devices or systems can't manage data gathering by the set of the sensors composite in a system through the phase of data preprocessing, origin of discriminative and salient characteristics, and data identification in the status of the body activity. In the present day, the clinicians usually perform the diagnoses and classification of the diseases, according to the information that has been obtained from many physiological sensor signals. None-the-less, the

sensor signal could be vulnerable easily to specific interference or noise cases and as a result of the large individual variation sensitivity to various physiological sensors might vary as well. Which is why, multiple sensor signal fusion is necessary for providing more reliable and robust decisions. [9].

1.2. Problem statement

In recent years, the world has been facing an increasing number of the illness and patients. Moreover, wars and the relationships between the human and animals led to introduce and spread new kinds of viruses and unknown diseases such as coved-19. Consequently, this will make heath observation and evaluation a complex task for the hospitals and medical staff. In addition, the connected health-care applications are facing some important challenges like saving the power of the biosensor devices to ensure a long time monitoring as possible for the patients, and speed up discovering of the patient's emergency and send it to the medical specialist to provide the suitable decision.

1.3. Thesis Objective

The main aim of this thesis is to reduce the consumed emerge of the biosensor devices to guarantee as long monitoring as possible for the patient and fast detecting of the patients emergency and report to the medical experts in order to provide the appropriate decision to save ther lives. Hence, in order to achieve the main aim, the following objectives are formulated:

- To design emerge efficient multisensory adaptive sensing and aggregation (EMASA) for patient monitoring in edge computing based IOHT.
- To evaluate the performance of the proposed approach in comparison with available solution in simulated environment.
- To verify and validate the proposed approach based on the results obtained from the simulation experiments that ensure the correctness of its implementation.

1.4. Main Contributions of this Thesis

i. An energy-efficient Multisensor Adaptive Sensing and Aggregation (EMASA) approach is proposed for Patient Monitoring in Edge Computing based IoHT Networks. The EMASA is applied on two levels in the Edge-based on IoHT network: biosensors and the Edge gateway.

ii. An integrated local emergency discovery with sampling rate adaptation is implemented at the biosensor level to remove the redundant data before sending it to the Edge gateway.

iii. A patient Health Evaluation with Decision-making (PaHED) algorithm is proposed at the Edge gateway level. The data of biosensor nodes are fused and the trained SVM model is employed to produce an accurate and fast decision according to the status of the patient.

iv. Various experiments are achieved by using a custom Python-based simulator. Real medical data are used during the simulation which are taken from the dataset named MIMIC I and MIMIC II (i.e. Multiple Intelligent Monitoring in Intensive Care) of Physio-Net [10]. The simulation time of each experiment is nearly two hours (70 periods). The performance of the EMASA approach is compared with Carol's method [11] to show the effectiveness of the proposed method.

1.5. Related Work

One of the effective solutions in hospitals is to use the connected health care to save and process the sensed vital signs of the patients to make the appropriate decision to save their lives. Some related work is focused on compression methods to reduce the huge data in Navarro, Gonzalo and Sara Kadhum, and Ali Kadhum Idrees [12, 13], aggregation in Al-Nassrawy, Kahlaa K., Dhiah Al-Shammary, and Ali Kadhum Idrees [14, 15] and prediction methods . B. O. Soufiene, et. Al in [16], was propose a technique named PCDA (Priority-based Compressed Data Aggregation) to minimize the medical sensed data. The authors employed compressed sensing with cryptography to compress the data while saving the quality of received data.

The work by Habib, Carol et.al in [17, 18, 19] presented an adaptive sampling with risk evaluation to decide for monitoring the patients by WBSNs. They proposed a framework to gather medical data by the biosensors and then introduce the risk of the patient using fuzzy logic. Finally, the presented an algorithm for deciding according to the level of patient risk, The results show that both approaches have coherently assessed the health condition of different Intensive Care Unit (ICU) patients. Yet, there proposed approach overcomes the other approach in terms of energy consumption (around 86% less energy consumption) and data reduction (around 70% for sensing and more than 90% for transmission). Shawqi and Idrees [20, 21] introduced a power-aware sampling method using several biosensors to provide the risk of the patient and the best decision to notify the medical experts. First, multisensory sampling based on the weighted scores model is introduced and then they suggested a decision-making algorithm that applied at the coordinator,

The results illustrate a decrease in the volume of gathered data, thus a significant energy saving has been made while preserving data accuracy and integrity.The works by Idrees, A. Makhoul, Al-Qurabat et.al in [22, 23, 24, 25, 26] proposed adaptive sampling approaches for WSNs. They have employed similarity measures and some data mining techniques to measure the similarity between two data set of two periods so as to change the sampling rate accordingly , that is, overhead reduction up to 67% in gathered data, 73% in transmitted data, and 78% in consumed energy while maintaining the accuracy of sent data as high as 94.6%..

In H. Harb et.al [27], the authors combine two efficient methods: divide and conquer (D&C) and clustering. They applied the D&C at the sensor nodes and then they applied the enhanced K-means at the cluster node to remove the redundant data and save energy before sending it to the sink, that approach can be effectively used to conserve energy in the sensor network and to increase its lifetime, while still keeping a high quality of the collected data..

In A. S. Abiodun et.al [28], the authors propose a classification technique based on a defined threshold where sensor's readings are classified into three types: urgent (above threshold), semiurgent (close to threshold) and nonurgent (less than threshold). Furthermore, the authors introduce a routing protocol for a medical sensor that enables transmitting packets during gateway failure, The performance evaluation of this work using OMNET++ with varied performance metrics shows promising results, because verification outperforms the extant state-of-the-art methods in terms of power consumption, packet delivery ratio, and the number of transmitted packets.

The authors in [12, 13] proposed lossless compression methods for compressing EEG data in IoT networks. In [12], they combine the fractal

compression method with differential encoding. In [13], the authors combine Huffman encoding and clustering to further reduce compressed data before sending it to the IoT network , The results show that there HCHE approach can introduce a better compression ratio in comparison with other approaches. HCHE can compress the EEG data in all records from 70% up to 83%. The other methods compress the EEG data in all records from 14% up to 56%, from 65% up to 70%, from 40% up to 54% for HCLZW, HE, and LZW respectively.

The authors in [29] proposed three main methods that can be executed at the s-Health architecture, namely, divided in-network processing and resource optimization, event detection and adaptive compression, and dynamic networks association. The first method optimizes medical information transport from the edge node to the healthcare supplier, however taking energy efficiency and application's goodness-of-service request. The second method uses edge computing capabilities to demonstrate an effective data transit architecture that ensures high reliability and rapid emergency reaction. The third method leverages heterogeneous wireless networks within the s-Health architecture to perfect various applications' requirements while optimizing energy consumption and medical data delivery, The results show that the model provides the best results for the different scenarios with up to 97% in terms of correct classification rate.

Abeer Al-Marridi, et.al in [30] proposed fixing the problem by taking advantage of rapid innovations in the fields of mobile phones, sensors and wireless technology to get better health systems is a critical method. M-Health system accommodates the usage of an edge device to communicate medical data through the wireless network across the m-Health station to diagnose and control the situation of the patient as quickly as possible.

Recently, the authors Koussaifi, Habib, et.al in [31, 32, 33] open a new trend in connected healthcare by proposing several frameworks for a real-time patient monitoring and assessment. In [33], a framework for a stress detection and evaluation has been proposed. The framework works by detecting first stress signals according to skin conductance parameter, then the stress level is evaluated through fuzzy inference system based on patient vital signs, particularly heart rate, respiration rate, and average blood pressure , The results show that the percentage of detected critical events and the mean-square error (MSE) are both acceptable. In addition, the percentage of data reduction is around 50% implying a reduction of the energy consumption.

Ref.No.	Method and Algorithm proposed	Evaluation Metrics	Simulation results
[12,13]	Lossless compression methods	The performance evaluation is achieved using diferent performance metrics such as Compression Ratio (CR), compression and decompression Computation Time, and size of transmitted data	The results show that there approach can introduce a better compression ratio in comparison with other approaches
[14,15]	Aggregation Method	Data Percentage after Employing Reduction, Energy Consumption, Accuracy of Data and Transmitted sets Percentage	The performance evaluation of the proposed DaReCA technique has shown better results compared with other approaches in terms of energy consumption at the sensor device and aggregator, data reduction, and accuracy

[16]	Prediction methods(PCDA) (Priority-based Compressed Data Aggregation)	Memory overhead, execution time, energy consumption and communication overhead	The results show great promise for PCDA in terms of security, energy efficiency and communication overhead
[17,18,19]	Adaptive sampling algorithm and fuzzy logic	Energy consumption and Data reduction	Result shows outperformed in terms of energy consumption and data reduction
[20, 21]	Introduced a power-aware sampling method and a decision-making algorithm	Data accuracy , data integrity energy consumption	The results illustrate a decrease in the volume of gathered data, thus a significant energy saving
[22-26]	Adaptive sampling approaches for WSNs	Consumed energy accuracy of sent data and data reduction	Result shows reduction up to 67% in gathered data, 73% in transmitted data, and 78% in consumed energy
[27]	Divide and Conquer (D&C) and clustering	Energy saving and collected data reduction and network lifetime	Result shows outperformed in conserve energy and to increase its lifetime, while still keeping a high quality of the collected data.
[28]	A classification technique and a routing protocol	The performance evaluation of this work using OMNET++ with varied performance metrics	Shows promising results, because verification outperforms the extant state-of-the-art methods in terms of power consumption

[29]	Optimizes, edge computing and	Energy consumption	The results show that the model provides the best results for the different scenarios
[30]	Healthchain-RL framework	The reward convergence of the proposed approaches, a Comprehensive comparison with different heuristic policies, the adaptation to sudden changes, and theconsumed action-time in real-time	The result show that reinforcement learning approaches outperform the Greedy and the Random-Selection (RS) approaches
[33]	A stress detection and evaluation and fuzzy inference system	Data reduction and energy consumption	The results show that the percentage of detected critical events and the mean-square error (MSE) are both acceptable

1.6. Organization of the Thesis

This thesis has been organized into 5 chapters. Chapter one presents a general introduction to the subject. Chapter two deeply covers Scientific Background of wireless sensor network and wbsn applications and challenges and explain data collection and fusion. Chapter three describes the framework of the proposed work and its level. Chapter four presents the obtaining Results, Analysis, and Discussions. Finally, chapter five presents Conclusion and Future Works.

2.1 Introduction

Interest in pervasive and ubiquitous healthcare solutions is currently increasing given the potential they have and the benefits they bring to people's everyday life. Wireless Body Sensor Networks (WBSNs) play a major role in this field since they enforce the remote and continuous monitoring of the health at a low cost and reduce unnecessary hospitalization as well as healthcare expenditure. WBSNs have the potential to detect and even prevent life-threatening health problems such as a heart attack. Many healthcare and well-being applications can be fulfilled using WBSNs such as: emergency detection, health assessment, disease prevention, medical diagnosis, tracking physical activity, mental health support etc, thus several populations are concerned: elderly, patients suffering from chronic diseases, acutely-ill patients, athletes and even any average person who is interested in continuously monitoring his/her health. These healthcare applications must satisfy multiple requirements to ensure user satisfaction such as good quality of service and accuracy**.**

A WBSN includes wireless sensor nodes that are called the biosensors and a coordinator. The former can be invasive or non-invasive. They sense and collect physiological signals such as Electrocardiogram (ECG), Electroencephalogram (EEG) and Photoplethysmogram (PPG) etc. and vital signs like the Heart Rate (HR), Respiration Rate (RR), skin temperature, oxygen saturation (SpO2), blood pressure (BP), etc. The latter is usually the person's smart phone or any other portable device. It manages the network, receives the collected signals/measurements and performs the data analysis and fusion to reach the healthcare's application goal.

2.2 Wireless Body Sensor Networks (WBSNs)

The WBSNs had emerged as an inexpensive solution allowing the continuous monitoring of the physiological and physical parameters of the human body. A lot of research has been made and is still being made in the design of medical accurate invasive and non invasive sensors and the design of comfortable wearable health monitoring systems. Firstly the most commonly employed sensors in WBSNs. capture physiological parameters including vital signs and physiological signals as well as physical parameters related to body movement. In Additionally to the discussion of the differences of several commercially available wearable sensor nodes on the market [34]. Having health related data being continuously Collected leads to a palette of body sensor network (BSN) applications. A particular focus is given to healthcare applications given that it is the main focus of this thesis. All types of population can benefit from BSN healthcare applications, starting from toddlers to elderly, depending on the monitoring phenomenon of interest. Furthermore, diverse monitoring tasks can be achieved such as event detection, prediction, diagnosis etc,

Thus a discussion about these tasks and depict them is provide as a function of three different dimensions: the type of user, the type of processing and the monitoring location However, BSN healthcare applications should meet a set of requirements in order to achieve user satisfaction, perform as desired, have an impact on people's life and ensurcontinuity, especially that WBSNs have limited resources, are subjected to interference as well as faulty measurements and that are dealing with sensitive medical data[26].

2.2.1. Wireless Body Sensor Networks (WBSN) Architecture

A WBSN consists of biosensor nodes and a coordinator, The former are deployed on a person's body. They may be either implanted inside the human body or placed on it. They continuously sense physiological signals, vital signs, An example of physiological signals include ECG, EEG and PPG etc. Whereas an example of vital signs include the RR, HR, temperature, BP and oxygen saturation etc. The acquired data is periodically and wirelessly transmitted to the coordinator of the network[35]. The latter can be any portable device close to a person's body such as his/her smartphone or PDA. Its role is to manage the network and perform the fusion of the collected data. Thus, emergencies, abnormal events as well as the continuous follow-up of the person's health condition can be ensured by the coordinator. Moreover, it can provide the person advice, reminders and take action in emergency situations such as call the doctor. The collected data as well as results of the process of fusion are sent by the coordinator to the medical center (healthcare experts, doctors) where further processing can be made. [35].

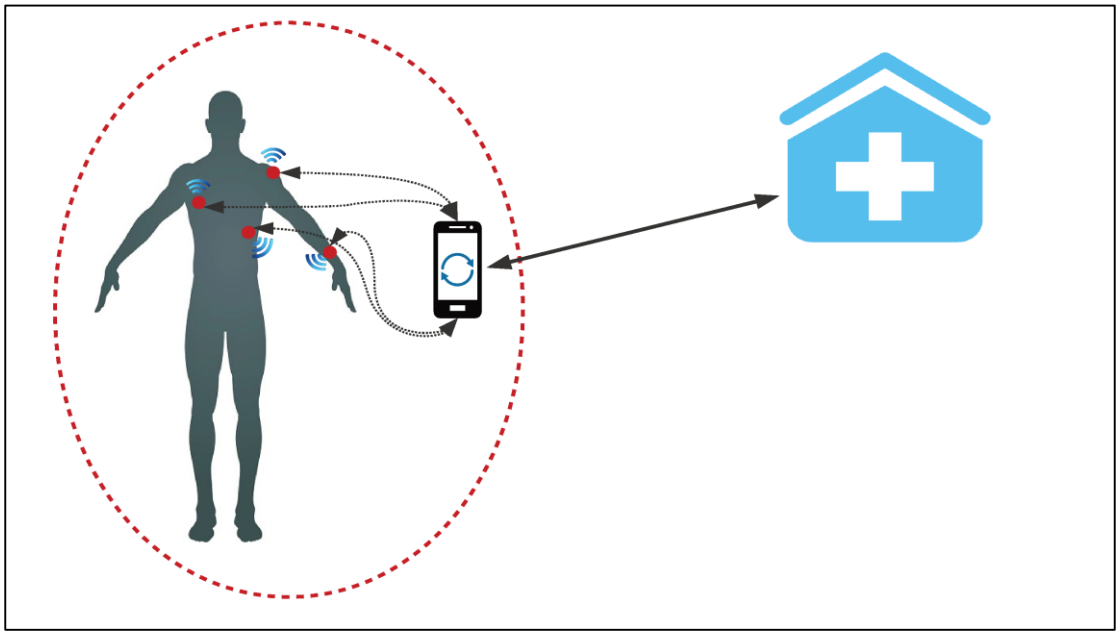


Figure 2.1: WBSN architecture [35].

2.2.2. Biosensor

Biosensors are miniature, lightweight, low power, limited-resources and intelligent sensor nodes that sense, process and transmit human physiological parameters such as the ECG, the heart rate, the body temperature, the body movement etc. Figure. 2.2 illustrates the components of a wireless biosensor node. It is composed of three units powered by a battery: the sensing, the processing and the transmission units [36].

All three units require power for performing tasks. However, the transmission has been viewed as the most power-hungry of tasks. The unit of sensing includes a sensor and an ADC, converting the analog signal that is sensed with a certain frequency (Nyquist-Shannon), to a digital signal.

The latter is given to processing unit (i.e. memory and processor) where the algorithms of processing are run. In addition to that, the processor regulates the transmission and sensing units and it changes and/or activates their status based on applications and utilized protocols. [36]

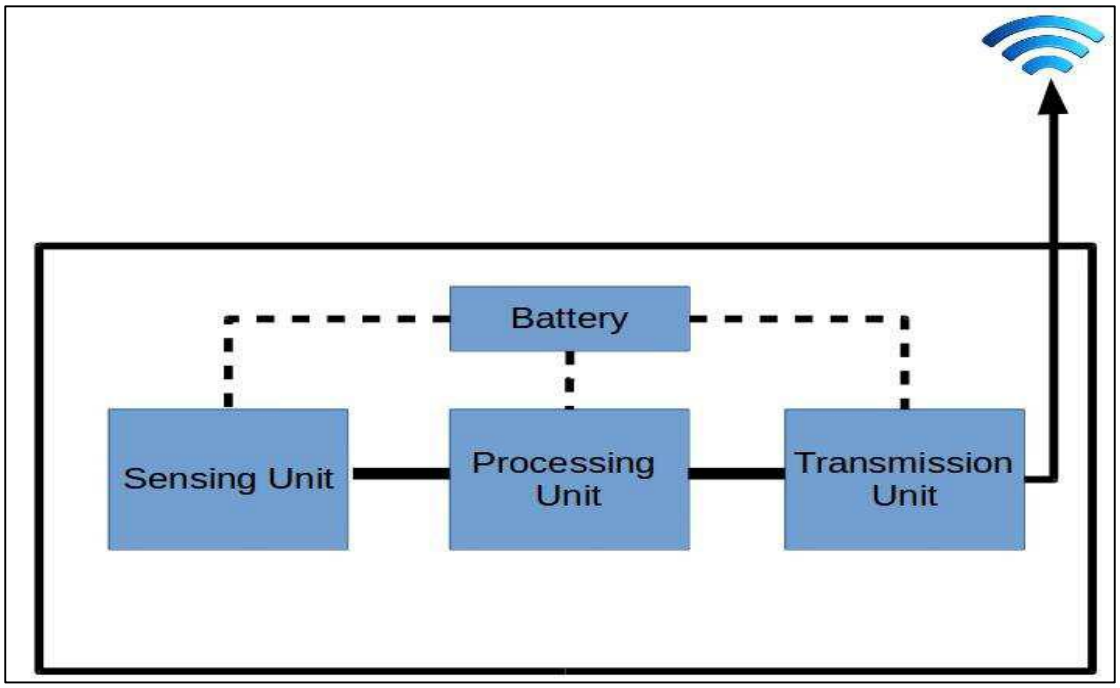


Figure 2.2: The components of a biosensor node [36].

2.3 WBSN Applications

These applications are comprehensive for multiple areas such as health care, assistance to the elderly and provision response to emergency case [37] An overview of potential medical applications will be presented in this section.

2.3.1 Telemedicine and Remote Patient Monitoring

Increasing cost of medical care and old age in the world's population leads to a major development in the telemedicine network for the purpose of providing many medical services. Telemedicine uses an integrated medical system and modern communication techniques to enable the delivery of a remote patient care service and also provides the possibility for health professional in the world such as physicians, scientists and others to take care of more patients. In this case, the patient can remain under the continuous monitoring of the doctor under normal physiological conditions without affecting the daily activities and at the lowest cost. WBSNs are able to supply constant monitoring for the biomedical parameters and failure detection in the devices when it occurs, as well as early detection of emergencies. Such patient monitoring systems will be more secure, more compatible and inexpensive [37].

2.3.2. Rehabilitation and Therapy

Aim of rehabilitation application is permitting for sick people after leaving the hospital to recover their functional abilities and return to normal condition by convenient treatment [37] Rehabilitation is a dynamic operation designed for correction any wrong behavior by using the available facilities to arrive the optimal state. In order to reach a person with a brain stroke to the highest level of stability, the movement of the patient during rehabilitation period should be constantly monitored and

corrected. Thus, patients' movement tracking becomes necessary in the scheme of rehabilitation [37].

2.3.3. Biofeedback

Biofeedback indicates to the possibility of measuring biomedical activity and potential medical parameters and returning them to the user in order to allow him to modify his biological activity and control it for the purpose of enhancing his health. It is beneficial for controlling certain conditions and for non- voluntary human body functions such as blood pressure plus migraines. The devices of biofeedback can involve those designed for monitoring the human heart functions, breathing apparatus, brainwaves and others [38].

2.3.4. Assisted Living Technologies

Aging in the world population and the high cost of formal healthcare institutions as well as the tendency of some individuals to live independently all this led to an expansion of innovative living techniques for an independent and secure aging. These application use house automation to enhance living and preserve an independent style for life.

Actually, supported living techniques have been used as an alternative for older people, people with special needs and disabilities persons who cannot be independent and the same time do not need health care all the time.

The ambient health sensor network can obtain the bio parameters of the environment of living and then send them to a centralized station due to medical constant monitoring system. The health of these people can be guessed by knowing the blood pressure, heart rate, etc. These systems could be linked to a medical center for the purpose of emergency response or sudden changes (if the parameters deviate from the physical range) [13].

2.4. Challenges of Wireless Body Sensor Network

1- Reliably – the major problem is to ensure that information reaches is intended destination in reliable manner. Many factors contribute to the reliability of wireless body sensor network, including stable software programing, dependable wireless communications between nodes sensor and efficient processing in every sensor node.

2- Biocompatibility – for sensors node that directly interact with patient body, the shape, size and materials are limited. Packaging the sensor in biocompatible materials is the solution.

3- Portably – the size and Wight of the sensors node employed in wireless physiology measuring device must be tiny and light Wight, whether they are placed on or swallowed.

4- Privacy and security – the major security concerns include eavesdropping, identity spoofing and disclosure of personal information to the unauthorized persons. It is possible to be secure improved by incepting data, privet data must be safeguarded against unauthorized access "Consented data acquisition, proper data storage, secure transmissions, and integrity of the data and authorized data access are vital areas for developing software or hardware solutions".[39]

5- Light-weight wireless communication protocols have to be able to handle self-organization networks (include security features) as well as data gathering and routing.

6- Enrage aware communication nodes should transmit at allow power level.to allow the nodes negotiate their transmission power to the minimum, an emerge-were protocol is required.

2.5. Data Collection

Data collection is a method of gathering and measuring data,that are collect from several source of information so as to supply answers to pertinent questions[40].

The process of gathering, measuring, and evaluation of the correct information for the study, utilizing approved established processes has been known as the data collection. According to the obtained facts, a study could evaluate the hypothesis. Despite the subject of study, the collection of data is typically the first and most important stage in the process of the research. For the dialysis, the different methods to the data acquisition are utilized in various disciplines of study, relying on the information needed[40].

The most significant aim of data gathering is collecting the information-rich and accurate data for the statistical analyses so that the data-driven study decisions could be made.

There are two type of data collection: primary data and secondary data, the primary data are un processed data that have been obtained for the first time. The secondary data represents the information that was gathered and tested already [41].

2.6. Data Fusion

Currently, developing intelligent algorithms for a variety of tasks in healthcare applications has been attracting the research community. Hence, the treatment and processing of the collected data is an important aspect in WBSNs. For instance, data fusion in WBSNs allows to combine, to correlate and to associate physiological data and medical information coming from one or multiple biosensor nodes in order to achieve accurate situation assessments about the monitored person. Particularly, multi-

sensor fusion has been gaining an ever-increasing interest driven by its potential in ensuring a unified picture about the health condition of the patient. However, several challenges exist in WBSNs, especially that the collected data is subject to noise, interference and faulty measurements, thus leading to the fusion of imperfect and inconsistent data.

Furthermore, real-time fusion and good accuracy, which are two important aspects in healthcare applications, should be satisfied by multi-sensor fusion approaches.

The Data fusion is multilevel operation that deals with associations, correlations, combination of the data and information from multiple as well as single sources for achieving the identity estimations, refined position، and complete timely evaluations of the situations, threats in addition to their relevance [42].

The following definition for Multisensor fusion enables to obtain a unified image and a globalized view of the system by combining information from several sources [43][44].

There are three different data fusion approaches based on the processing architecture are identified: distributed, centralized and hybrid. The centralized method depends on a fusion center where all processing is carried out. A distributed method is adopted when the sensor nodes perform independent processing on the data they have captured and transmit the results to a fusion node. In this case, the fusion node executes a global analysis based on the results sent by all the sensor nodes [45, 46].

Finally, hybrid fusion concerns approaches where the sensor nodes only perform pre-processing and/or perform partial lightweight computation on the collected data in a distributed approach fashion while a central node fuses the gathered data and performs high-level fusion [47].

2.7 Early Warning Score

The medical staff in the hospital utilizes a physiological scoring system named National Early Warning Score (NEWS) to check the situation of the patients to provide the appropriate medical attention and the proper care for the cases with high levels of risk. There are six physiological parameters included in the NEWS that exhibit this system of scoring such as RR, temperature, oxygen saturation, systolic blood pressure, PR, and awareness level or new contingency [48]. The main feature of NEWS is its simplicity in determining the risk level of the patient using the suitable scores for each type of biosensor. By scoring the sensed values of these biosensors, the NEWS can determine the status of the patient [49]. EMASA mechanism will apply NEWS at each biosensor. The NEWS is displayed in Table1 [50].

Table 1 NEWS (National Early Warning Score).

Physiological parameters	3	2	1	0	1	2	3
Respiration Rate	≤ 8		9-11	12-20		21-24	≥ 25
Oxygen Saturations	≤ 91	92-93	94-95	≥ 96			
Any Supplemental Oxygen		Yes		No			
Temperature	≤ 35		35.1-36.0	36.1-38.0	38.1-39.0	≥39.1	
Systolic BP	≤ 90	91-100	101-110	111-219			≥ 220
Heart Rate	≤ 40		41-50	51-90	91-110	111-130	≥ 131
Level of Consciousness				A			V.P.orU

2.8. Edit Distance (ED)

Edit Distance (ED) is a method to measure the similarity between two strings and also named as Levenshtein distance [36]. Algorithm 2.1 shows the dynamic programming algorithm for computing the edit distance between two sets of data.

The similarity between the scores of two periods in the round is calculated according the edit distance.

- **Algorithm 2.1 Edit Distance**

Input :

Mset1, Mset2: measures for two sets of 2 periods.

Output :

Mdp: distance between the Mset1 and Mset2.

1: Mdp ← 0
2: For i ∈ Len(Mset1)+1 do
3: For j ∈ Len(Mset2)+1 do
4: if i = 0 then
5: $Mdp_{i,j} \leftarrow j$
6: else if j = 0 then
7: $Mdp_{ij} \leftarrow i$
8: else if $Mset_{i-1} = Mset_{j-1}$ then
9: $Mdp_{i,j} \leftarrow Mdp_{i-1,j-1}$
10: else
11: $Mdp_{i,j} \leftarrow 1 + \min(Mdp_{i,j-1}, Mdp_{i-1,j}, Mdp_{i-1,j-1})$
12: endif
13: endfor
15: endfor
16: return $Mdp_{Len(Mset1), Len(Mset2)}$

Function Len(x) return the length of the set x. The time complexity of the edit distance is Θ(Len(Mset1), Len(Mset2)) and the storage complexity is Θ(Len(Mset1), Len(Mset2)) and this can be improved to Θ(min(Len(Mset1), Len(Mset2))) by observing that the algorithm at any instant requires two columns (or two rows) in the memory storage.

2.9. Support Vector Machines (SVMs)

In the past few years, a massive amount of the researches was performed on the SVMs and their applications in a number of areas in science. SVMs have been considered as a very robust and powerful regression and classification algorithm in several of the application areas. SVMs have been playing an important role in the problem of pattern recognition which is one of the extensively active and popular research areas amongst researchers [51].

SVM one of the common tools of supervised machine learning, it is commonly utilized for the efficient classification. The SVMs demonstrate high accuracy of the classification with many applications, like the object detection, speech recognition, bio-informatics, image classification, medical diagnosis, and so on. [52]. The supervised machine learning is typically composed of 2 fundamental stages, learning/training phase and classification phase. The training phase of the SVMs constructs a model to be utilized to classify any testing data which has been based upon the Support Vectors (SVs).

Support Vectors have been identified from training data-set throughout the process of the training, to be utilized then in the phase of the classification for the prediction of proper class of input testing data. The SVMs showed high rates of the classification accuracy, as they outperform other common algorithms of classification in a wide range of the

applications and cases [53, 54]. There is a growing interest for the exploitation of the SVMs in several of the embedded systems of detection and different applications of image processing.

SVM represents a powerful algorithm for machine learning, showing high precision in various problems of classification [55]. The SVMs are based upon the theory of decision boundary, efficiently differentiating between 2 different data sample classes. There are two main phases in this model of supervised learning, training/learning and classification phases. In phase of training, a trained model is advanced with the use of input training data-set, where a decision boundary has been formed from optimal separating hyper-plane which optimally separates the data samples of those 2 classes. SVs represent data samples which lie on decision boundary, and they have been defined in the phase of the training and are utilized after that for the tasks of the classification in classification stage.

The reason for using the SVMs in machine learning The SVMs are utilized in some applications such as the hand-writing recognition, face detection, intrusion detection, gene classification, e-mail classification, and in web pages. It is a reason for using the SVM in machine learning. It has the ability of handling the classification as well as the regression on the linear and the nonlinear data. An additional reason for using the SVMs is due to the fact that they have the ability of finding complex relationships between one's data without needing to perform many transformations on their own. It is one of the best options in the case of working with smaller data-sets having tens-hundreds of thousands of the features. Usually, they find more precise results in comparison with other algorithms due to their capability in handling small, complex data-sets [56]. Below is a set of advantages and disadvantages for utilizing the SVMs.

a. Advantages:

- Effective with the data-sets with several features, such as the medical and financial data.
- Utilizes a sub-set of the training points in decision function that has been referred to as the SVs, making it memory efficient.
- Effective in the cases in which the number of the features is higher compared to the number of the data points.
- A variety of kernel functions may be specified for the decision function. Common kernels may be used, however, there is a possibility as well specify the customized kernels.

b. Disadvantages

- In the case where the number of the features is considerably bigger than the number of the data points, avoiding the over-fitting in the case of selecting the kernel functions and regularization terms are vital.
- Operates optimally on the small sample datasets due to its long training durations.
- The SVMs do not provide estimates of probability directly. Which are estimated with the use of an expensive 5-fold cross-validation.

In phase of the classification, the main function of classification/decision (1) is utilized for the classification of the new test data $\vec{x}$ (dimensional vector), depending upon number of the support vectors n. (α, y, & b represents the parameters that are specified in the phase of the training.

$$f(x) = sin\left(\sum_{i=1}^{n} ai.yi.K(\vec{x}i, \vec{x}) + b\right)$$

This function comprises complex computation between every one of the SVs denoted as ⃗xi and test vector ⃗x that is carried out by a kernel trick K. The common utilized kernel functions include [57, 58]:

- $linearK(\vec{X}i, \vec{X}) = \vec{X}i.\vec{X}$ 2.1
- $Polynomial\ K(\vec{X}i, \vec{X}) = (\vec{x}i.\vec{x})^n$ 2.2
- $Sigmoid\ K*(\vec{x}i, \vec{x}) = \tanh(\vec{x}i.\vec{x} + \theta)$.....2.3
- $Gaussion\ radial\ basis\ function(RBF)$:.....2.4

$$K(\vec{x}i, \vec{x}) = e^{(\frac{-\|\vec{x}i - \vec{X}\|^2}{2\sigma^2})}$$

- $Hardware - friendly\ K(\vec{X}i, \vec{X}) = 2^{-y\|K(\vec{X}i, \vec{X})\|1}$.....2.5

Originally, the SVMs are a binary classifier, whereas multi-class classification has been based upon the multi-binary SVMs. Various approaches are utilized for the realization of the multi-class SVM classification as “one-against-all” and “one-against-one” [59].

2.9.1. Performance Evaluation Measures for Svm model

` There are so many performance evaluation measures when it comes to selecting a classification model

1. Confusion Matrix:

Confusion Matrix usually causes a lot of confusion even in those who are using them regularly. Terms used in defining a confusion matrix are TP, TN, FP, and FN.

- **True Positive (TP):**

This is called TP or True Positive. This is because the case is positive in real and at the same time the case was classified correctly.

- **False Positive (FP):**

This is called FP or False Positive. This is because the case was actually negative but was falsely classified as positive

- **True Negative (TN):**

This is called TN or True Negative. This is because the case was actually negative and was also classified as negative which is the right thing to do.

- **False Negative (FN):**

This is called FN or False Negative as the case was actually positive but was falsely classified as negative.

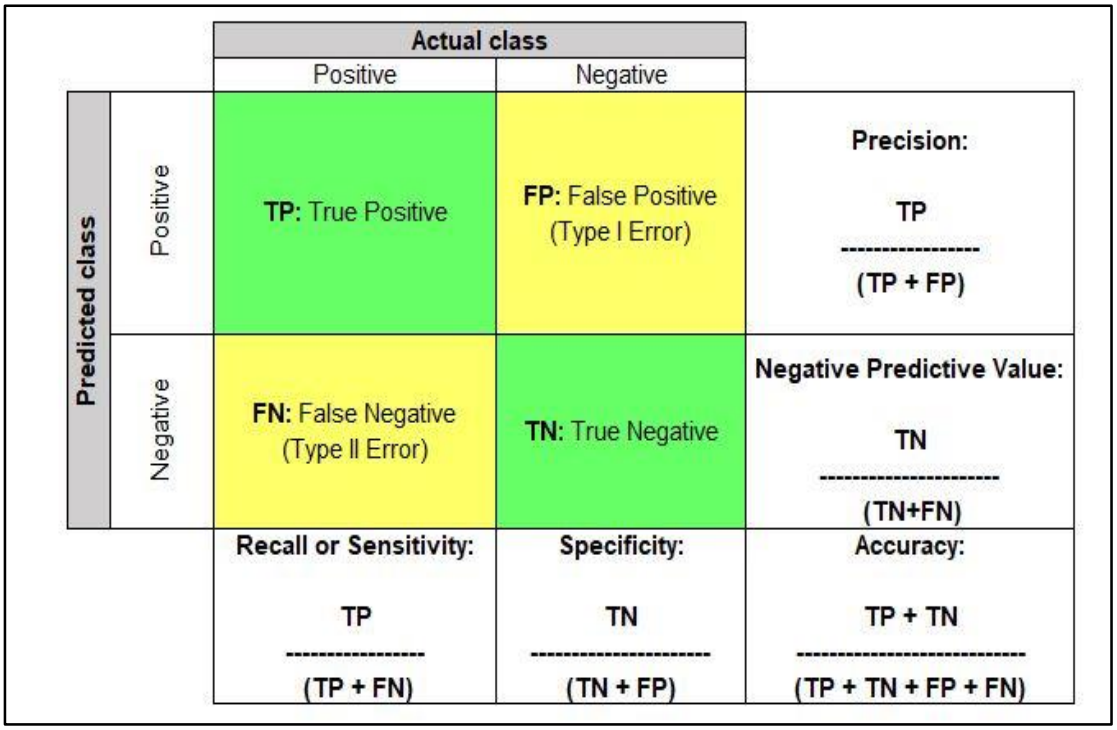


Figure (2.3) explain how a confusion matrix looks like.

2. Accuracy:

Accuracy = (TP + TN) / (TP + FP +TN + FN)

This term tells us how many right classifications were made out of all the classifications. In other words, how many TPs and TNs were done out of

TP + TN + FP + FNs. It tells the ratio of "True"s to the sum of "True"s and "False"s.

3. Precision:

Precision = TP / (TP + FP)

Out of all that were marked as positive, how many are actually truly positive.

4. Recall or Sensitivity:

Recall = TP/ (TN + FN)

Out of all the actual real positive cases, how many were identified as positive.

5. F1-Score:

F1 score = 2* (Precision * Recall) / (Precision + Recall)

As we saw above, sometimes we need to give weightage to FP and sometimes to FN. F1 score is a weighted average of Precision and Recall, which means there is equal importance given to FP and FN. This is a very useful metric compared to "Accuracy". The problem with using accuracy is that if we have a highly imbalanced dataset for training (for example, a training dataset with 95% positive class and 5% negative class), the model will end up learning how to predict the positive class properly and will not learn how to identify the negative class. But the model will still have very high accuracy in the test dataset too as it will know how to identify the positives really well.

- **Macro Average**

Macro averaging is perhaps the most straightforward amongst the numerous averaging methods. The macro-averaged F1 score (or macro F1 score) is

computed by taking the arithmetic mean (aka unweighted mean) of all the per-class F1 scores.This method treats all classes equally regardless of their support values

- **Weighted Average**

The weighted-averaged F1 score is calculated by taking the mean of all per-class F1 scores while considering each class's support. Support refers to the number of actual occurrences of the class in the dataset. For example, the support value of 1 in Boat means that there is only one observation with an actual label of Boat.The 'weight' essentially refers to the proportion of each class's support relative to the sum of all support values. With weighted averaging, the output average would have accounted for the contribution of each class as weighted by the number of examples of that given class.

- **Micro Average**

Micro averaging computes a global average F1 score by counting the sums of the True Positives (TP), False Negatives (FN), and False Positives (FP).We first sum the respective TP, FP, and FN values across all classes and then plug them into the F1 equation to get our micro F1 score.

2.10. Energy Consumption Model

This model can be characterized as the design and analysis of mathematical representation of the WBSN for studying the effects of the alteration of the parameters of the system. The behavior of this model represents a function of its parameters [22]. The reduction of power that is consumed in the communication by the wireless sensor nodes may be highly effective, due to the fact that radio transceiver is a component with maximum power consumption. The wireless sensor node is comprised of three components that are powered by battery: the sensing, the processing

and the transmission units. All those three units need power for performing their tasks. The energy consumption of this thesis was evaluated based on typical power consumption concerning wearable node, where 1 energy unit equals 152 Joules: the task of the sensing consumes 6 Joules, the task of processing consumes 24 Joules, transmission task (TX) consumes 60 Joules and receiving task (RX) consumes 62 Joules [60].

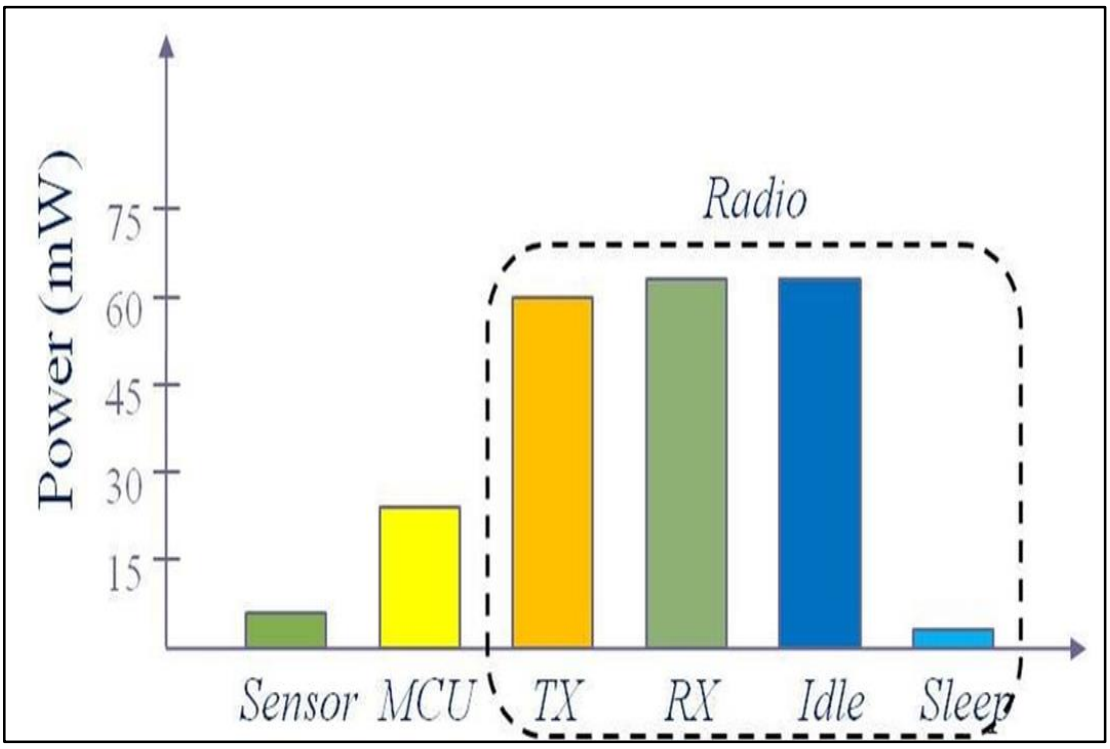


Figure 2.3: Typical Power Consumption in Wearable Nodes [23].

The present work assumes that total initial energy of the sensor node will be randomly fixed to units; where energy of sensing task consumed 0.04 units *(6/152 ≈ 0.04)*, 0.16 energy units for processing task *(24/152 ≈ 0.16)*, 0.40 energy units for transmission task *(60/152 ≈ 0.4)* and 0.40 units of energy for receiving task *(62/152 ≈ 0.4)*. Furthermore, the total initial energy in the WBSN is calculated to all vital signs of interested. Therefore, total energy will be N×units where N can be equal to 2, 3, 4 or 5 biosensors.

2.11. Performance Metrics

2.11.1 Instantaneous Sampling Rate Adaptation

Since the data that have been collected through sensor nodes is usually redundant and includes a high correlation, then adaptive data gathering method is therefore seen to be an essential processing procedure to save energy within WBSNs. This method mainly aims at decreasing the amount of data gathered in WBSNs, as well as permitting nodes to change their rate of sampling in light of a patient's dynamic risk level within area of monitoring. Therefore, it can be concluded that huge efforts have been made in research recently concerning the performance of this metric.

This is because of the computation power and the bandwidth provided through the infrastructure of the WBSN which is in general evaluated as inadequate. In addition to that, setting sampling rate fixed at too high value results in rising the amount of the consumed energy, whereas in some of the cases, setting sampling rate at low value could result in enlarging the amount of the lost information, in the end, creating a likelihood of the unexpected critical events.

2.11.2. Percentage of Data Reduction

This metric investigates process of the reduction of data that is performed at the level of the sensor node which is based upon adaptation of the sampling rate, and discusses its impact upon losing the information over the suggested period. The percentages are depict the ratios in both adaptive sampling and non-adaptive sampling. These percentages are taken according to the experiment conducted thoroughly in this study.

2.11.3. Energy Consumption

The function of the biosensor device is sending signals with biological significance about the condition of the patient to medical staff for the

purpose of creating actual medical diagnosis, which allows them to make correct decisions. The increase in the WBSN device functionality has resulted in a subsequent increase in demands of power, due to the fact that the process of data transmission is quite energy-consuming. In addition to that, an additional challenge that has been faced is the diversity of the data that has been collected (heart rate, RR, BP, and so on), and several security and privacy problems [61]. Determined by the activity of the user and the goals of the application, the device can switch amongst a number of the energy saving modes corresponding to certain unit component setups (in other words, the sensor sampling rate, transceiver power state or microcontroller configuration, and so on). In spite of the high number of the energy management approaches have proposed to address this problem, however, those aren't applicable to the WBSNs as a result of the difference in the properties of the network.

2.11.4. Data Integrity

This part observes data integrity in two aspects. The first is comparison for the sensed data amount and distribution of score between sensed and original data-sets. As well, the importance of this metric ensures a high degree of the precision and integrity of obtained data where no score may be replaced or lost after application of the rate of sampling. Which is why, the decisions that have been made by a coordinator aren't influenced.

2.12. Summary

In this chapter, an overview about biosensors that are used in WBSNs has been provided. On the one hand, different types of biosensors exist depending on wear ability and the type of signal. A lot of research is still needed in order to design more accurate and fine-grained biosensors that take advantage of different sensing technologies such as capacitive sensing and PPG sensing. Furthermore, smart watches, textiles and patches are

currently gaining a lot of interest due to their ease of wear ability and their future potential in healthcare applications. On the other hand, WBSN enable the development of diverse healthcare applications. These applications are able to provide different monitoring tasks. This thesis particularly tackles health assessment, event detection and decision-support. However, healthcare applications should meet several requirements given that WBSNs have many constraints and that we are dealing with medical data.

3.1. Introduction

The rapid development in the Internet of Things (IoT) led to increasing advancement in the healthcare industry. The development in the hardware platform, as well as the underlying software, led to the emerging Internet of Healthcare Things (IoHT). The demand for remote healthcare continuous monitoring systems using limited resources biosensors is increased. These biosensors will increase the collected and transmitted data across the IoHT network. Therefore, decreasing the gathered data and make a decision at the Edge gateway can save the energy of biosensors and produce a quick response to the medical staff. This chapter focuses on suggesting the appropriate techniques to deal with these challenges in the IoHT.

3.2. EMASA Technique

This thesis propose an Energy-efficient Multisensor Adaptive Sensing and Aggregation (EMASA) for Patient Monitoring in Edge Computing based IoHT Networks. EMASA is implemented at two level in the IoHT network: biosensors and Edge gateway, The EMASA is executed in the medical biosensors to eliminate unnecessary data during controlling and observing the situation of the patients. It functions in rounds. The round includes two periods. The emergency detection and modifying the sampling rate of each biosensor are two main steps in the EMASA. The NEWS is achieved at each biosensor to drop the repeated data before delivering it to the Edge gateway. The sampling rate is adjusted after every two periods based on the situation of the patient at the end of each round. Figure 1 shows the EMASA approach.

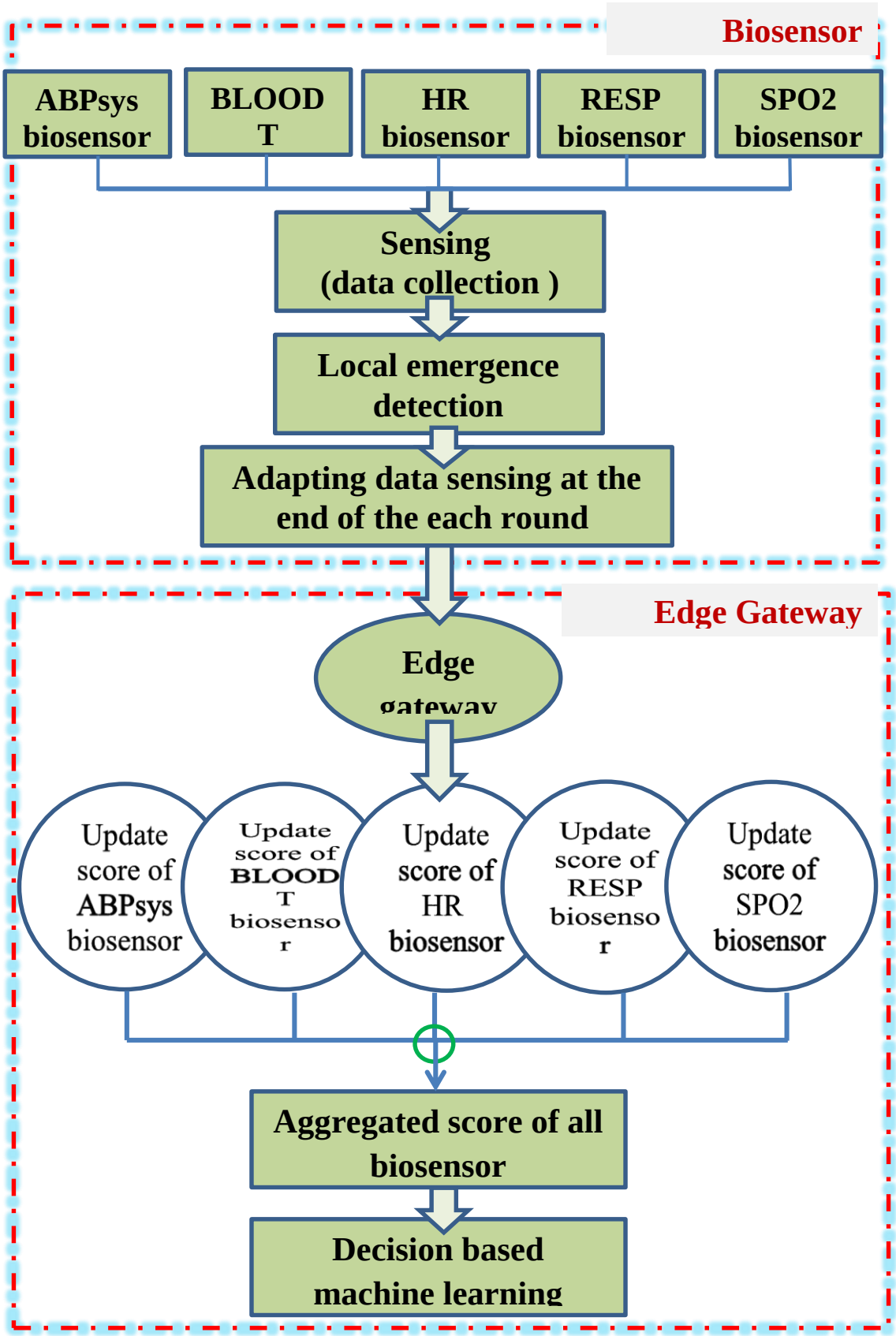


Figure 3.1 the proposed EMASA approach.

EMASA approach executed the proposed EASeT technique at the biosensor level. Then, it aggregates the received data from the biosensor nodes and updated them and learn the machine learning based SVM to use it to provide an accurate and fast decision to prevent a critical situation that led to patient death by sending a notification message to the medical staff.

3.2.1. Biosensor Nodes Level

In biosensor devices, the collected data is reduced, the local emergency is locally identified, and the sampling rate is adapted per round (two periods) according to the patient situation. This section explains the main functions that applied in the biosensor in more details.

A. National Early Warning Score

The medical staff in the hospital utilizes a physiological scoring system named National Early Warning Score (NEWS) to check the situation of the patients to provide the appropriate medical attention and the proper care for the cases with high levels of risk. As it is mentioned before ,there are six physiological parameters included in the NEWS that exhibit this system of scoring such as respiratory rate, oxygen saturation, temperature, systolic blood pressure, pulse rate, and awareness level or new contingency. The main feature of NEWS is its simplicity in determining the risk level of the patient using the suitable scores for each type of biosensor. By scoring the sensed values of these biosensors, the NEWS can determine the status of the patient. EMASA mechanism will apply NEWS at each biosensor. The NEWS is displayed in Table 1 in chapter two [64].

B. Emergency Detection of the Patient

In medical applications, the vital singe of the patients are sensed using several biosensors (e.g., Oxygen Saturation, Heart Rate, Respiration Rate, etc.) located on the body of the patients. These biosensors send in the

periodic way each sensed measurement to the Edge gateway. The Edge gateway receives huge sensed measurements in each period. Hence, the data reduction at each biosensor is essential before transmitting them to the Edge gateway. Applying data reduction at the biosensors can save energy and extend the lifetime of the monitoring system. Moreover, it can reduce the volume of received data at the Edge gateway to facilitate the analysis to provide an accurate decision about the situation of the patient.

According to NEWS, the biosensors send to the medical staff just the measurements with scores larger than 0. The measurements of the normal state of the patients will not be transmitted to the Edge gateway. It is clear that periodic monitoring for the situation of the patient will be reduced as well as the transmitted measurements to the Edge gateway are decreased. Finding the relations among the sensed measurements per period before forwarding them to the Edge gateway can participate in solving this problem .

The present work applied the algorithm of emergency detection for the patients at every biosensor inspirited from with some adjustments to test the scores of sensed measures and forwarding the ones with scores higher than 0. The emergency detection approach is presented in Algorithm 3.1.

- **Algorithm 3. 1 Emergency Detection of Patient**

Input:

MR: Gathered measures in one period

Output:

FM: Forwarded measures, SR: scores for forwarded measures

1: P_s ← NEWS(MR1)
2: FM ← FM ∪ MR1
3: SR ← SR ∪ P_s
4: ForwardToGateway(MR1)
5: EnergyUpdateForBiosensor()
6: For each sensed measure MRi ∈ FM do // i = 2,3, …, N
7: C_s ← NEWS(MRi)
8: If C_s ≠ P_s then
9: SR ← SR ∪ C_s
10: FM ← FM ∪ MRi
11: ForwardToGateway(MRi)
12: EnergyUpdateForBiosensor()
13: P_s ← C_s
14: end if
15: end for
16: return FM, SR

To further understand the emergency detection technique, an illustrative example will be presented.

Example :

Suppose there are ten measures of Respiration Rate biosensor and the period size(T)=10, MR = [16, 16, 14, 10, 11, 11, 21, 22, 24, 25]. By using NEWS,

the score's vector of MR measures is SR= [0; 0; 0; 1; 1; 1; 2; 2; 2; 3]. The forwarded measures by the medical sensor are [16, 10, 21, 25]. Only the critical measures and the first measure (even if it was 0) are forwarded to the medical expertise by the biosensor.

C. Adapting Sensing Frequency

The accumulated sensed measures of every medical sensor are time-correlated according to the situation of the patient. Consequently, when the patient's situation is stable, a lot of measures would be transferred to the gateway. There are three levels of risk for the patient: (1) low risk represents the normal case of the patient that wants low care by the medical staff. (2) Medium risk represents the middle case between the critical and normal situation of the patient that wants high care by the medical staff, and (3) high risk represents the severe illness cases of the patient that needs consecutive monitoring.

The sensed measures by the biosensors are time-correlated especially in the cases of high or low risk. Therefore, sending a large volume of sensed measures by the biosensors leads to spending the energy and increasing the load on the medical staff. To get rid of this problem, it is possible to adjust the sampling rate of the biosensor during sensing the measurements and according to the situation of the patient.

The proposed sampling algorithm in EMASA approach operates in the way of rounds, where each round includes two periods. Hence, the similarity rate should be calculated by the sampling algorithm between the

scores of the measures of the two periods. The edit distance is used to calculate this similarity between the two periods. Edit Distance (ED) is a measure of similarity that calculate the distance between two strings. It is also named Levenshtein distance . Algorithm 2.1 in chapter two shows the dynamic programming algorithm for computing the edit distance between two sets of data.

Algorithm 3.2 presents the adaptive sensing rate achieved at every biosensor at the end of the round.

- **Algorithm 3.2 Adaptive Sampling rate Algorithm**

Input:

SM_1, SM_2: two measures' sets for (2 periods), AS_{min}: minimum sensing rate, AS_{max}: maximum sensing rate

Output:

AS_{rate}: new sensing rate

1: *Dist* ← Edit Distance (SM_1, SM_2)

2: *Dist* ← Length(SM1) - Dist

3: *SimR* ← Dist/ AS_{max}

4: AP_{samp} ← (1 - SimR) * 100

5: If $AP_{samp} < AS_{min}$ then

6: $AS_{rate} ← AS_{min}$

7: *Else*

8: $AS_{rate} ← (AS_{max} * AP_{samp})/100$

9: *End* if

10: *Return* AS_{rate}

3.2.2. Edge gateway Level

In this level of the EMASA approach, the received data from the biosensors are processed, updated, aggregated and then taking the decision based on SVM.

A. Biosensor updated Score

The Edge gateway will receive several readings during each period from the biosensors. It calculates the updated score value for each received reading from each biosensor. Hence, the updated score US_t^k of biosensor k at time t is computed as follows.

$$US_t^k = \frac{US_{t-1}^k + US_t^k}{2} \quad \text{----------} \quad 3.1$$

Where US_0^k refers to the first reading transmitted by biosensor k to the Edge gateway in the period, US_t^k refers to the reading of biosensor k at the current time t, and US_{t-1}^k is the updated score of biosensor k that calculated at the time t-1. For instance, assume that the biosensor 1 transmits the score 0 at the time 0 (t=0). Then, it sends the score 1 at the time 1 (t=1). Hence, the update score of the biosensor 1 at time 1 is equal to 0.5.

B. Aggregated score of Biosensors

The aggregated score of the biosensors is used by the medical staff and experts to evaluate the situation of the monitored patient. Table 2 shows the chart of clinical response.

Table 3.1 the chart of clinical response.

NEW Score	Frequency of monitoring	Clinical Response
0	**Minimum 12 hourly**	• **Continue routine NEWS monitoring**
Total 1-4	**Minimum 4-6 hourly**	• **Inform registered nurse, who must assess the patient.** • **Registered nurse decides whether increased frequency of monitoring and/or escalation of care is required.**
3 in single Parameter	**Minimum 1 hourly**	• **Registered nurse to inform medical team caring for the patient, who will review and decide whether escalation of care is necessary.**
Total 5 or more Urgent response threshold	**Minimum 1 hourly**	•**Registered nurse to immediately inform the medical team caring for the patient.** • **Registered nurse to request urgent assessment by a clinician or team with core competencies in the care of acutely ill patients.** • **Provide clinical care in an environment with monitoring facilities.**
Total 7 or more Emergency response threshold	**Continuous monitoring of Vital signs**	•**Registered nurse to immediately inform the medical team caring for the patient-this should be at least at specialist registrar level.** •**Emergency assessment by a team with critical care competencies, including practitioner(s) with advanced airway management skills.** •**Consider transfer of care to a level 2 or 3 clinical care facility, ie higher-dependency unit or ICU.** •**Clinical care in an environment with monitoring facilities.**

This chart includes five cases of the patient risk level ranging from the normal state and growing to the critical case. The calculated aggregated score (AS) (see Eq. 3.2) is compared with values in the column of the NEWS score. If the situation of the patient represented by AS is located in any of the five cases, there are appropriate clinical responses and frequency of monitoring for each case.

Aggregated score AS is calculated by summation of the whole updated scores of the biosensors. It indicates the criticality level of the patient and in addition the mode of the intervention that must be applied. The AS of biosensors is calculated as follows.

$AS = \sum_{k=1}^{NB} US^k$ ---------- 3.2

Where NB is the number of biosensors that deployed on the body of the patient and the US^k is the updated score of biosensor k (see Eq.3.1).

C. Decision Making

After receiving the readings of the biosensor nodes that executing the emergency detection algorithm, the Edge gateway achieves the fusion for the readings of biosensor nodes to provide meaningful information about the situation of the patient health.

This health condition of the patient is utilized to assess the health risk of the patient and then take the appropriate decision. The Edge gateway transmits the taken decision and the collected data to the experts in the medical center. The Edge gateway collects the first readings of biosensor nodes at the beginning of each period, then each time t receives reading from appropriate biosensor k, it computes its updated score US. Finally, the Edge gateway calculates the aggregated score AS for the whole biosensor nodes using their updates scores. For example, if the Edge gateway only receives the scores of the biosensor nodes HR, RESP, and ABPsys at the time t, it calculates the updated score for them. Then, it uses the last saved updated score of the remaining two biosensor nodes BLOODT and SpO2. Finally, it computes the aggregated score. Algorithm 3.3 explains the Patient Health Evaluation with Decision-making (PaHED) that employed at the Edge gateway.

- **Algorithm 3.3 PaHED Algorithm**

1: **For each round r ∈ R do // (r = 2 periods)**
2: **For each Biosensor k do**
3: $US_0^k \leftarrow GetFirstScore(k)$;
4: **End for**
5: **For each received score in period do**
6: **For each Biosensor k do**
7: **If (biosensor k sent this score) Then**
8: $US_t^k \leftarrow \frac{US_{t-1}^k + US_t^k}{2}$;
9: **Else**
10: $US_t^k \leftarrow$ GetLastSavedUS^k(k);
11: **Endif**
12: **Endfor**
13: **Compute** $AS \leftarrow \sum_{k=1}^{NB} US_t^k$;
14: $D_j \leftarrow SVM\_Model(US, AS)$;
15: **Send NotPacket(**D_j**) to Experts;**
16: **Endfor**
17: **Endfor**

In Algorithm 3.3, the steps 2-4 used to receive and save the first score of each biosensor k (for each period) in the updated score US_0^k using function GetFirstScore (k). The steps from 6-12 will be applied when the Edge gateway receives one or more scores from the biosensors. The updated score of biosensor k US_t^k at the Edge gateway will be updated using step 8 if it received the score of that biosensor. Otherwise, the other biosensor(s) that not transmitted their score to the Edge gateway, their updated score at

the Edge will be taken as the last saved updated score at the Edge for these biosensors using function GetLastSaved US^k(k) as in step 10. The step 10 computes the AS using the Updated scores of the biosensors. The Edge gateway makes the suitable decision using a machine learning approach-based Support Vector Machine (SVM) classifier. The SVM is a powerful algorithm-based machine learning, which gives high precision and accuracy in various problems of classification. The data samples in the training dataset are used to train the SVM model. After the training process, the support vectors are obtained from the training utilized by the trained SVM model to classify/predict any new data. In this supervised learning model, two phases are found: training and classification/prediction. In the training phase, the SVM model is trained with the input training data samples. The boundary of decision is produced by optimally separating the hyper plane. This is done by separating the data samples of the different classes in a best way. The Support vectors refer to the data samples that located on the boundary of decision. The training phase defines these SVs that used later in the classification phase. In the SVM, the decision function is represented as [68]:

$$DF(\vec{v}) = Sign\left(\sum_{j=1}^{M} \alpha_j \, l_j \; \mathbf{KF}\left(\vec{v}, \vec{s_j}\right) + \boldsymbol{\beta}\right) \quad \text{---------- 3.3}$$

Where the α_j refers to the weight coefficient of each SV, l_j represents the class labels of the SVs, $\vec{s_j}$ refers to the SVs, $\vec{v}$ is the vector of input, $\mathbf{KF}\left(\vec{v}, \vec{s_j}\right)$ is the selected kernel function, and $\boldsymbol{\beta}$ is the bias parameter. The most popular kernel functions are defined as follows.

- Linear: $\mathbf{KF}\left(\vec{v}, \vec{s_j}\right) = \left(\vec{v} \cdot \vec{s_j}\right)$ ---------- 3.4
- Polynomial: $\mathbf{KF}\left(\vec{v}, \vec{s_j}\right) = \left(\boldsymbol{\gamma} \cdot \left(\vec{v} \cdot \vec{s_j}\right) + \boldsymbol{r}\right)^{\boldsymbol{d}}, \boldsymbol{\gamma} > \mathbf{0}$ ---------- 3.5
- Sigmoid: $\mathbf{KF}\left(\vec{v}, \vec{s_j}\right) = \boldsymbol{Tanth}\left(\left(\vec{v} \cdot \vec{s_j}\right) + \emptyset\right)$ ---------- 3.6

▪ Radial Basis Function: $\mathbf{KF}(\overrightarrow{v}, \overrightarrow{s_j}) = \boldsymbol{Exp}\left(\frac{\|(\overrightarrow{v} - \overrightarrow{s_j})\|^2}{2 \cdot \sigma^2}\right)$ ---------- 3.7

The SVM model is trained based on a collected dataset of more than 9 hours for five biosensor nodes deployed on the body of the patient. This dataset includes six features: $US^1, US^2, US^3, US^4, US^5$, and AS. The labeled class of each of input (features) is represented as the decision's number according to the Table 3. This table is based on the chart in Table 2. The SVM model is implemented by Python programming language using the "sklearn" library of machine learning. The proposed machine learning-based SVM model is evaluated by K-Fold cross-validation using a limited dataset. It is used to predict the experience of the SVM model on the unobserved data. The K-Fold cross-validation evaluates the SVM model on limited samples to see how can the model performs when utilized to produce predictions on the sample data that is not used during the model training. It is resulted in a mean of the model experience scores.

Table 3.2 The decision's number, AS, and clinical risk

Decision's Number	Aggregated Score (AS)	Clinical Risk
1	< 1	Low
2	1- 4.99	Low–medium
3	3 in one biosensor node	Medium
4	5 - 6.99	Medium-High
5	≥ 7	High

Hence, after training this model, it can be used later to predict the required decision according to the status of the patient.

3.3 Summery

This chapter presents an Energy-efficient Multisensor Adaptive Sensing and Aggregation (EMASA) for Patient Monitoring in Edge Computing based IoHT Networks. The EMASA is applied at two levels: biosensors and Edge gateway. The biosensor achieves the emergency detection and sampling rate adaptation by using EASeT technique to reduce the transmitted data to Edge gateway and detect the local risk of the patient. The Edge gateway aggregates the readings of the biosensors and then provides an accurate decision according to the situation of the patient using a machine learning-based SVM model.

4.1. Overview

Several experiments are introduced in this chapter using a custom simulator-based on Python programming languages and with using real medical data collected from Multiple Intelligent Monitoring in Intensive Care (MIMIC) databases of PhysioNet [69]. Several patient records and their vital signs (heart rate (HR), respiration rate (RESP), systolic blood pressure (ABPsys), blood temperature (BLOODT), and oxygen saturation (SpO2)) are employed in these experiments that assumed each vital sign is monitored by a single biosensor node. The following subsections will explain the experiment results for the two contributions introduced in this thesis. The proposed approaches are compared with an existing approach for evaluating the whole performance of the presented methods.

4.2. EASeT Technique Result

In this level, we will introduce the simulation results of the proposed EASeT technique that work on the biosensor nodes level. that have used some performance measures to evaluate the proposed EASeT technique such as the adaptation of sensing rate vs data reduction, energy consumption, and data integrity. EASeT is compared with an existing method that introduced by Habib et al. named modified LED. In this simulation, the proposed EASeT used a period of length 100 seconds and 70 periods (two hours). The Smin and Smax are 10 and 50 measures per period respectively. EASeT used record 267n of the patient and the experimentations are only performed on the respiration biosensor considering both high and low-risk conditions into account.

4.2.1. Adaptation of Sensing Rate vs Data Reduction

In this experiment, the sensing rate adaptation of the biosensor and the reduction in the transmitted data is studied. Figures 4.1 presents the conducted results of the proposed EASeT technique and for two types of patients: normal (a) and critical (b) that compared with modified LED* for the same types of patients (c) and (d). In figure 4.1 (a) and (b), the blue and orange colours represent the number of sensed data and number of transmitted data respectively after implementing the EASeT technique.

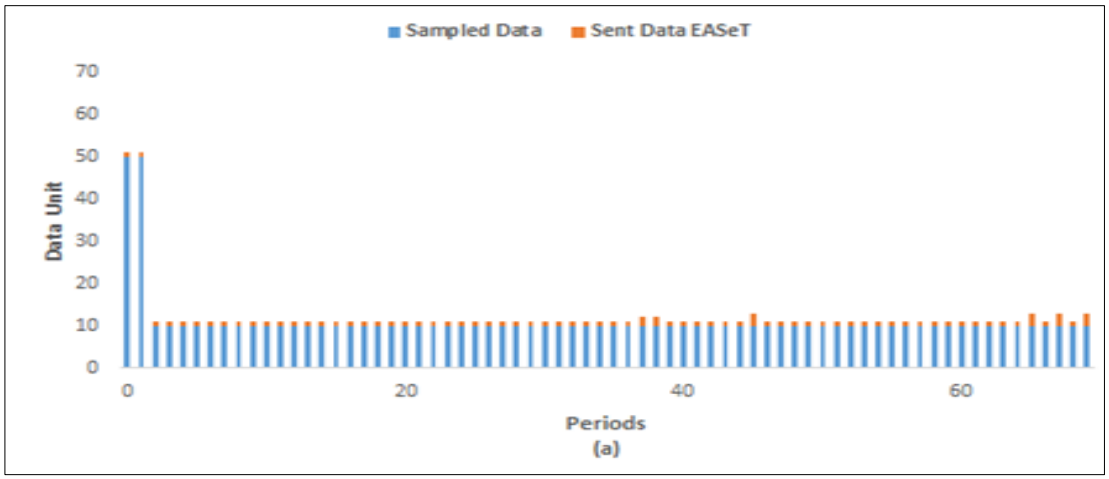


Figure 4.1 adaptation of sensing rate vs data reduction: a) low-risk patient

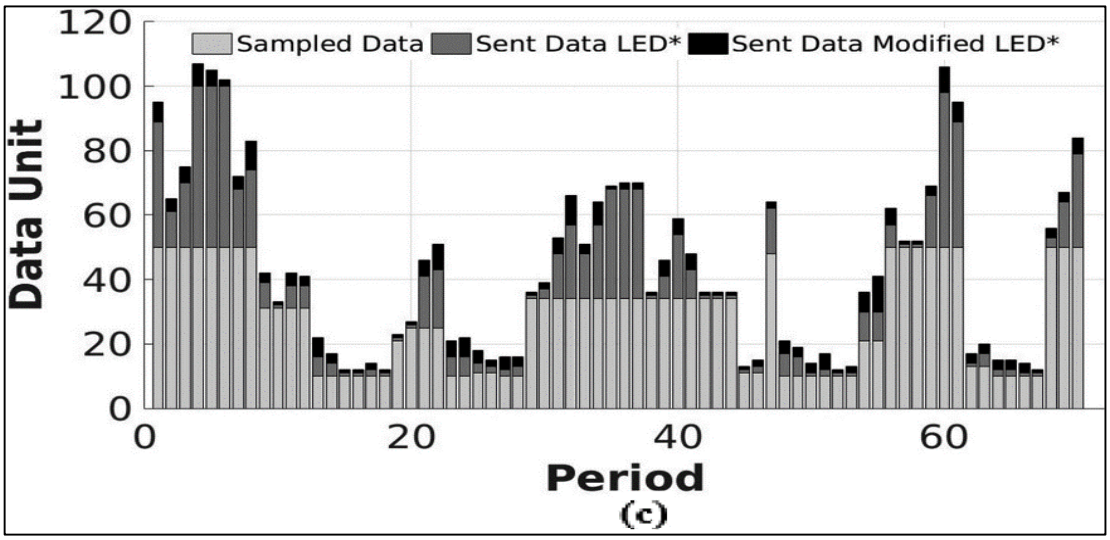


Figure 4.1 adaptation of sensing rate vs data reduction: (c) low-risk patient.

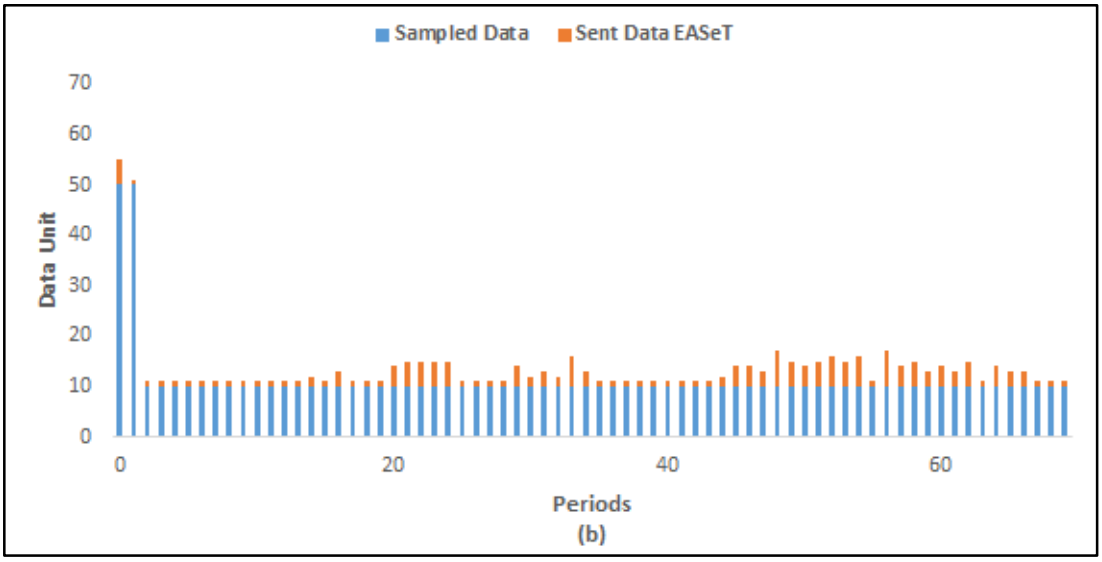


Figure 4.1 adaptation of sensing rate vs data reduction: (b) high-risk patient of EASeT .

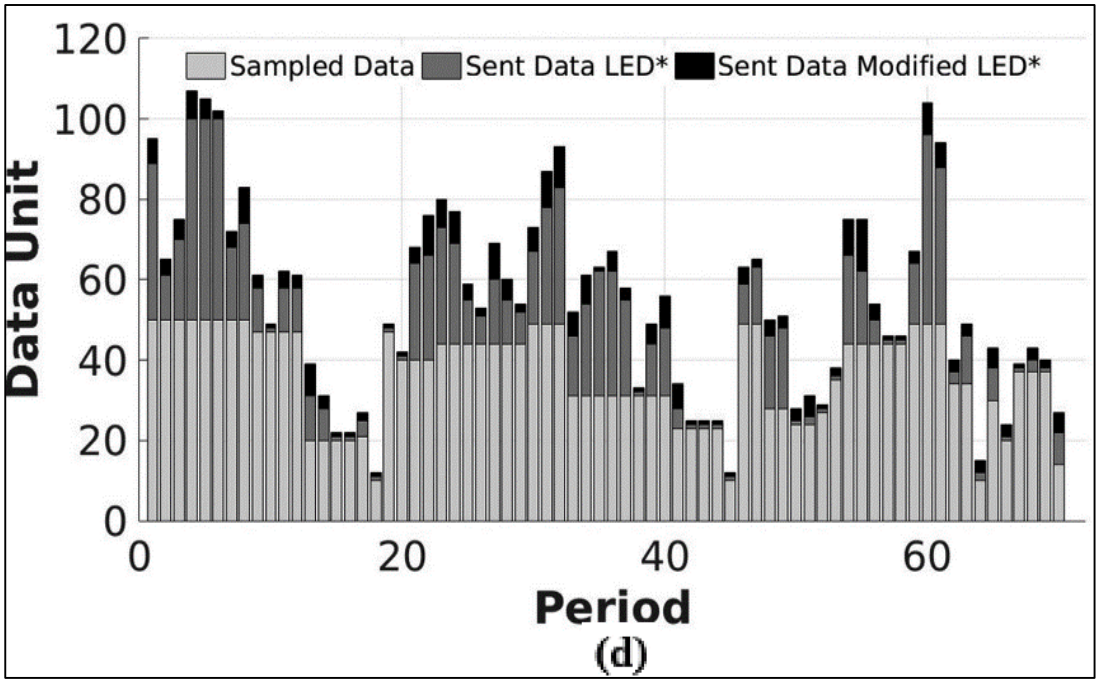


Figure 4.1 adaptation of sensing rate vs data reduction, (d) high-risk patient of the modified LED.

In figure 4.1 (c) and (d), the light grey and black colours represent the amount of sensed data and the number of transmitted data respectively after applying the EASeT technique. The dark grey colour in Figure 4.1 (c) and (d) was neglected that refers to the original method of LED.

The results in figure 4.1 (a) and (b), show that the amount of sensed data is changed to a minimum due to the similarity between the scores values of the sensed data of the two periods in both normal and critical cases of the patient. Besides, EASeT decreases the volume of sensed data using the emergency detection approach by eliminating the redundant data during each period before sending it to the coordinator for both normal and critical patients. As shown in Figure 4.1 (b), the transmitted sensed data is larger than Figure 4.1 (a) because it refers to the high-risk case of the patient. It has been shown in Figure 4.1 that EASeT ((a) and (b)) have a better performance than modified LED* ((c) and (d)) by reducing the amount of data transmitted to the coordinator and adapting the rate of sensing of the biosensor to the minimum.

4.2.2. Energy Consumption

This section studies the consumed power inside every biosensor and according to the situation of the patient (see Figure 4.2). In this experiment, EASeT is used the same energy parameter values of the modified LED*, where the initial energy of the biosensor is 700 units and the energy spend during sensing and transmitting one measure by the biosensor is equak to 0.1 and 1 respectively.

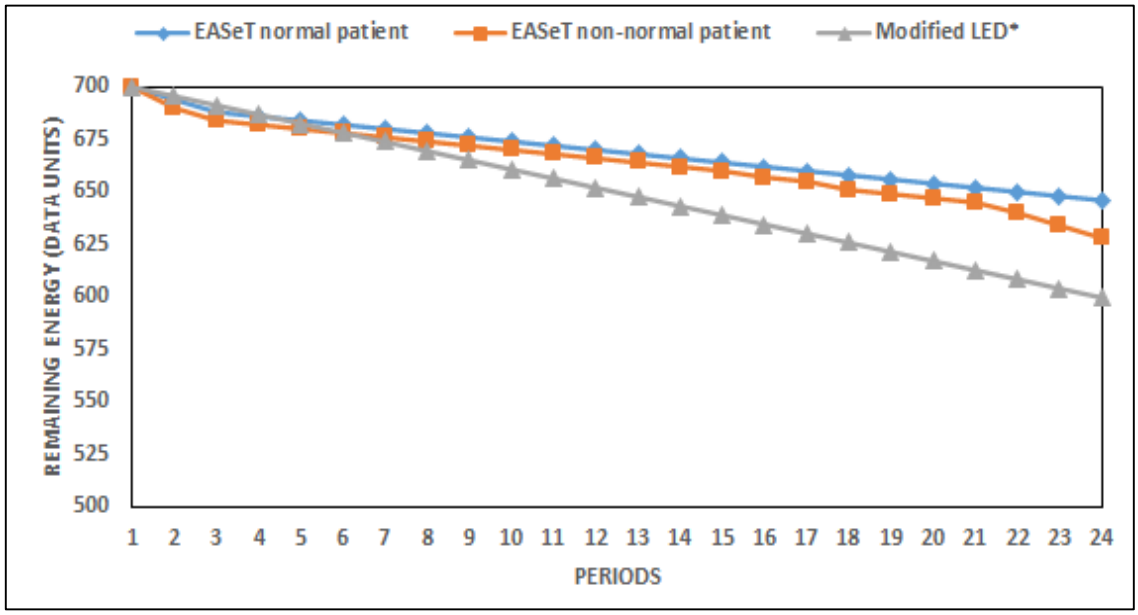


Figure 4.2 Energy consumption.

The energy consumption of the biosensor is affected by the volume of the sampled (sensed) data and the transmitted data to the coordinator. Since the proposed EASeT technique reduces the size of the sampled and transmitted data to the coordinator, it will highly outperform the modified LED* in term of the consumed energy of the biosensor.

4.2.3. Data Integrity

This section studies the effect of the proposed EASeT technique on data integrity. EASeT presents the results for two cases: normal and critical patients (see Figure 4.3 a and b), while the results of the modified LED* for a normal patient presented in Figure 4.3 c.

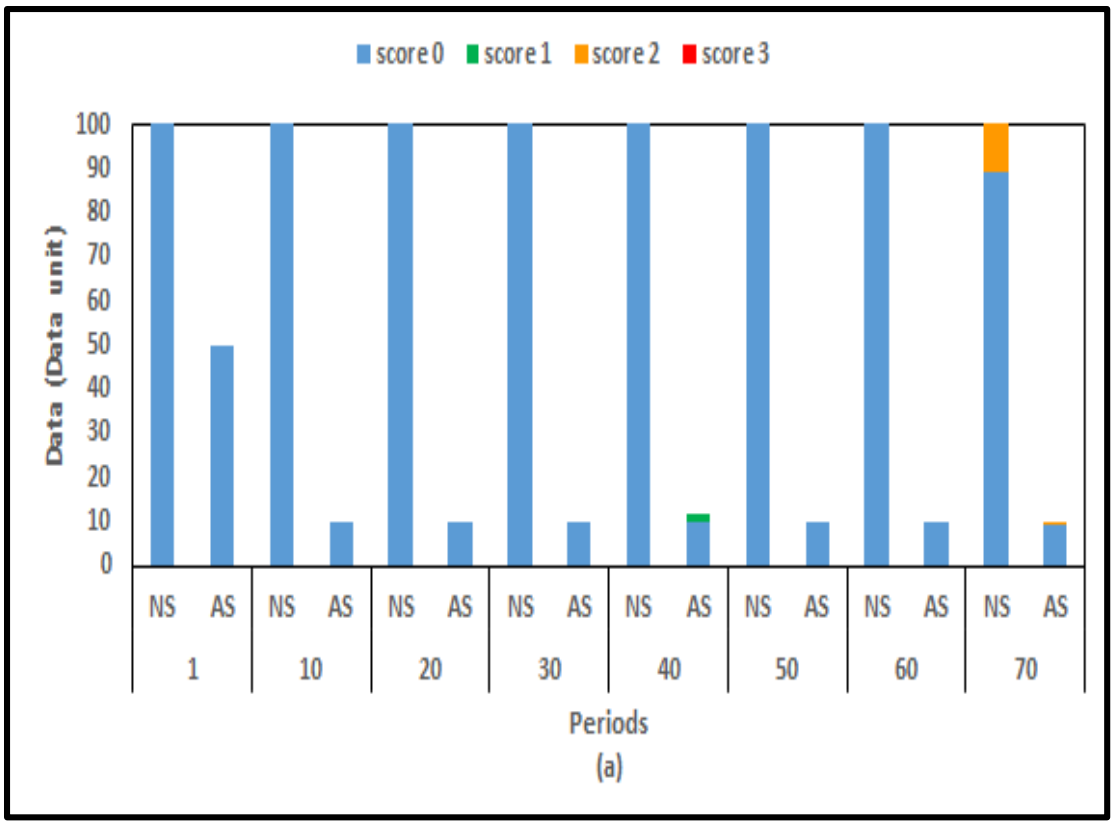


Figure 4.3 Data integrity: (a) low-risk patient

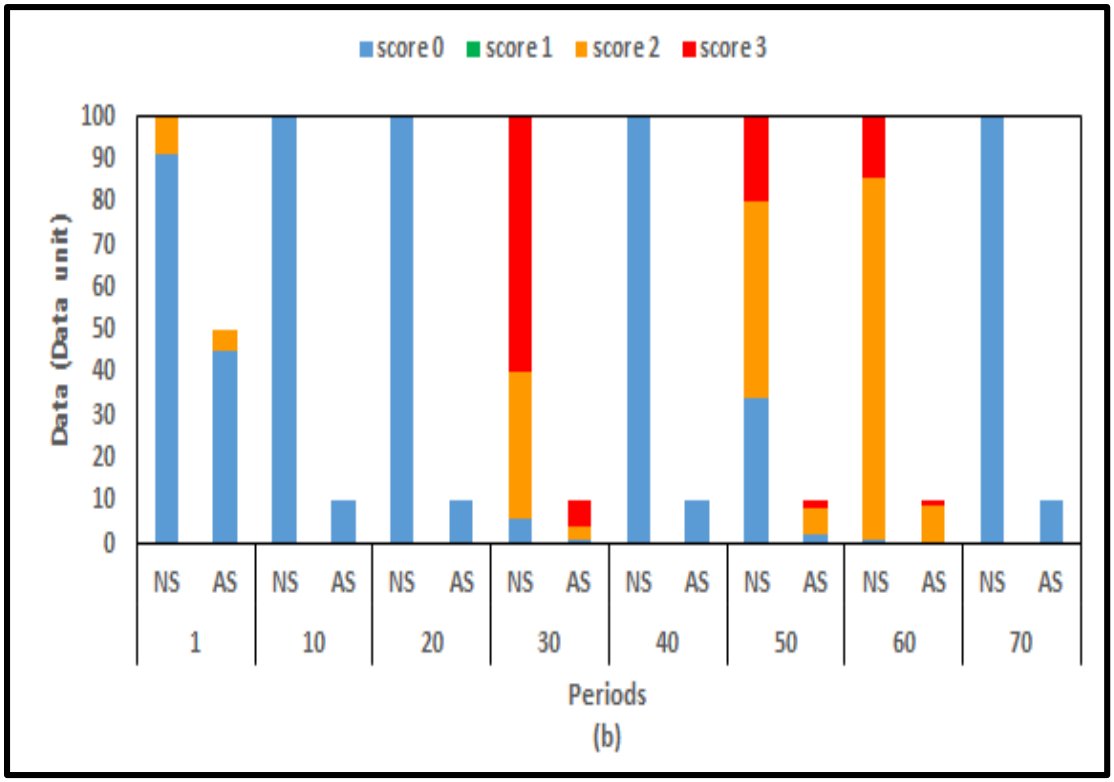


Figure 4.3 Data integrity(b) high-risk patient of EASeT,

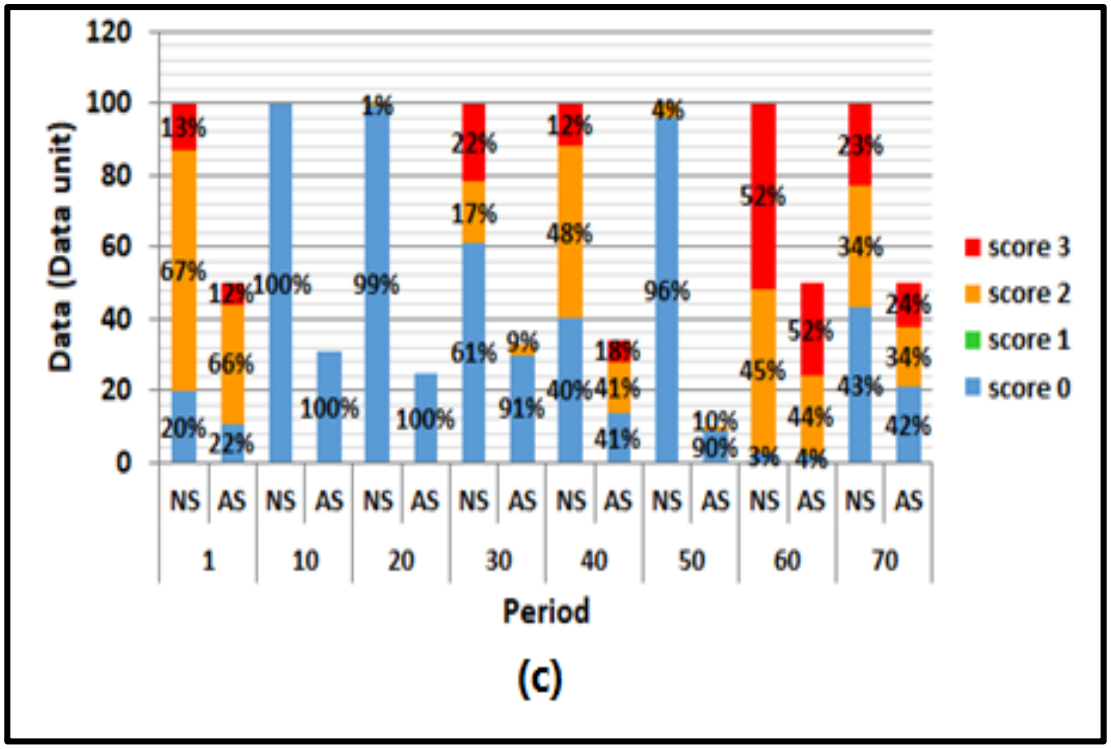


Figure 4.3 Data integrity: (c) low-risk patient of the modified LED.

This experiment is achieved based on the gathered data of every period without (NS) and with (AS) executing the adaptive sensing rate on the biosensor. It is achieved through scores distribution comparison (NEWS). Eight periods are selected from 70 periods to show the sensed data size and their distributions of scores with and without using adaptive sensing rate at the biosensor. It can be seen from the results in Figure 4.3 a that the EASeT technique reduces the sensed data for eight periods up to 85% in comparison with modified LED* (see Figure 4 c) that reduced the data up to 64.5% for a normal patient. In the case of the normal patient, the types of the score are limited to the score 0. This leads to a high reduction in the sensed data of the biosensor. Besides, the EASeT technique reduces the sensed data for eight periods up to 85% while maintaining a suitable representation of all scores at the coordinator. Hence, it can be regarded that EASeT ensures a good level of data integrity of the gathered data while keeping the whole scores without loss at the coordinator.

4.3. EMASA Technique Result

The performance evaluation of the proposed EMASA approach is introduced in this section. The simulation time of each experiment is nearly two hours (70 periods). Table 4 shows the values of parameters used during the simulation.

Table 4.1The values of parameters used during the simulation

Parameter	Value
P	100 Second
R	2 * P (70 periods) ≅ 2 Hours
ASmin	30 readings/period
ASmax	70 readings/period (1 reading/ 1.43 second)

The simulation results of EMASA are conducted based on two records of patients: Patient 1 with the record s01840-3454-10-24-18-46n of MIMIC II dataset and patient 2 with the record 276n of MIMIC dataset. These records are selected due to the comparison purpose with the Carol's method . The EMASA is evaluated using some performance measures like energy consumption, the adaptation of sensing rate vs data reduction, data integrity, etc. The dataset of the patient 1 includes the readings of the five biosensor nodes while the dataset of the patient 2 includes the readings of the four biosensor nodes where the "RESP" is not found.

4.3.1. Sampling Rate Adaptation

In this experiment, the sampling rate adaptation is investigated for various biosensor nodes in patient 1 and patient 2 and over 70 periods. Figures 4.4 (a) and 4.5 (a) show the sampling rate adaptation of the HR biosensors for both cases of patient 1 and patient 2 in comparison with the Carol et al. method. The results explain that the proposed EMASA adapted

the rate of sampling to the minimum due to the high similarity between the readings of the two periods in the round and for both patients 1 and 2. Consequently, the adapted sampling rate did not impact the transmitted scores to the Edge gateway that represent the status of the patient in the case of the local risk in the HR biosensor. The EMASA adapts the sampling rate of each biosensor node after the end of the second period of each round. Figures 4.4 (b) and 4.5 (b) introduce the sampling rate adaptation of the Carol et al. method. They adapted this rate based on the ANOVA model and the behavior function (BV). The EMASA approach produce a better performance than Carol's method by reducing transmitted readings to the Edge gateway via decreasing the sampling rate in the case of the high similarity between each two periods.

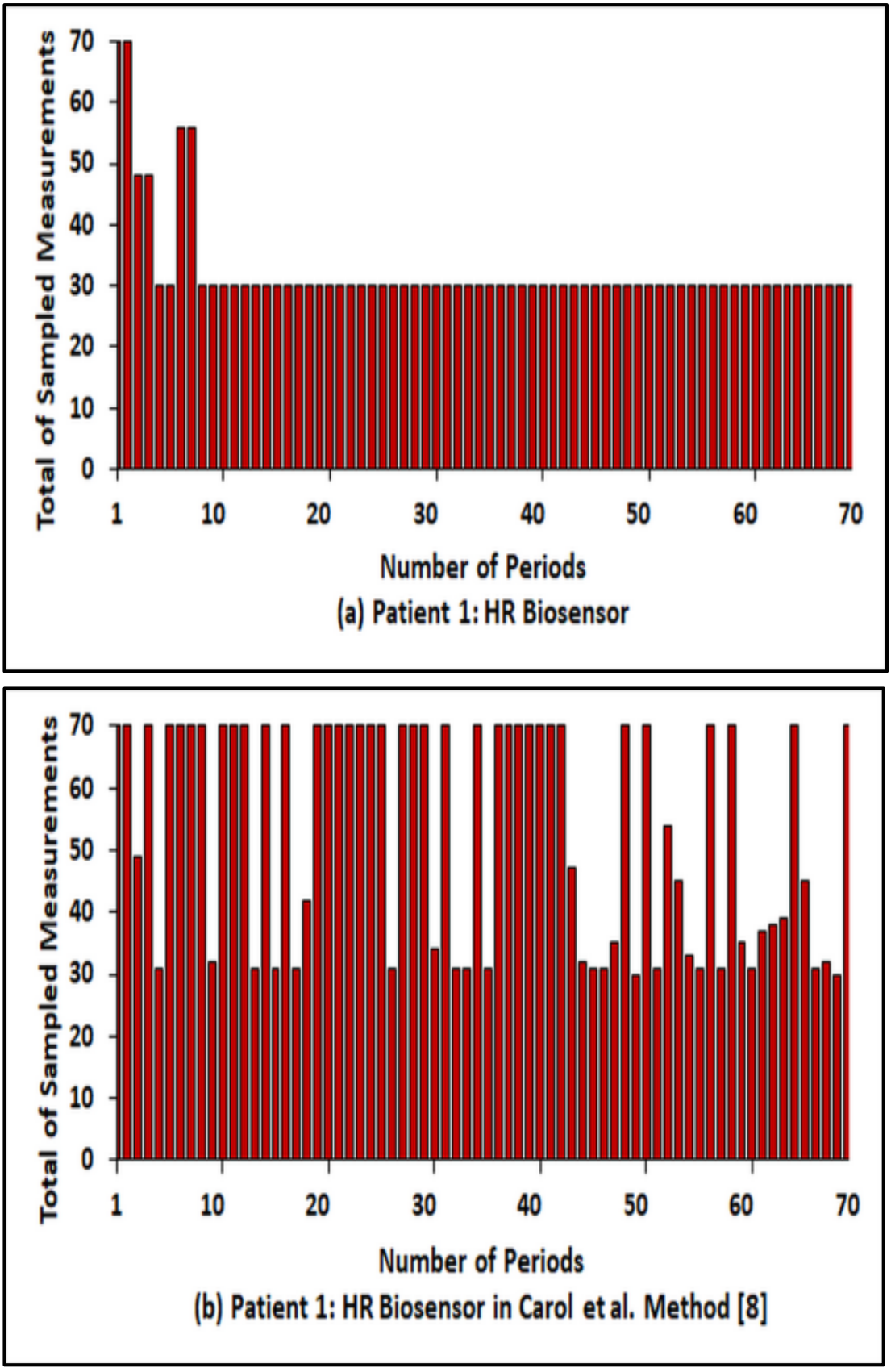


Figure 4.4 sampling rate adaptation (a,b) for patient 1.

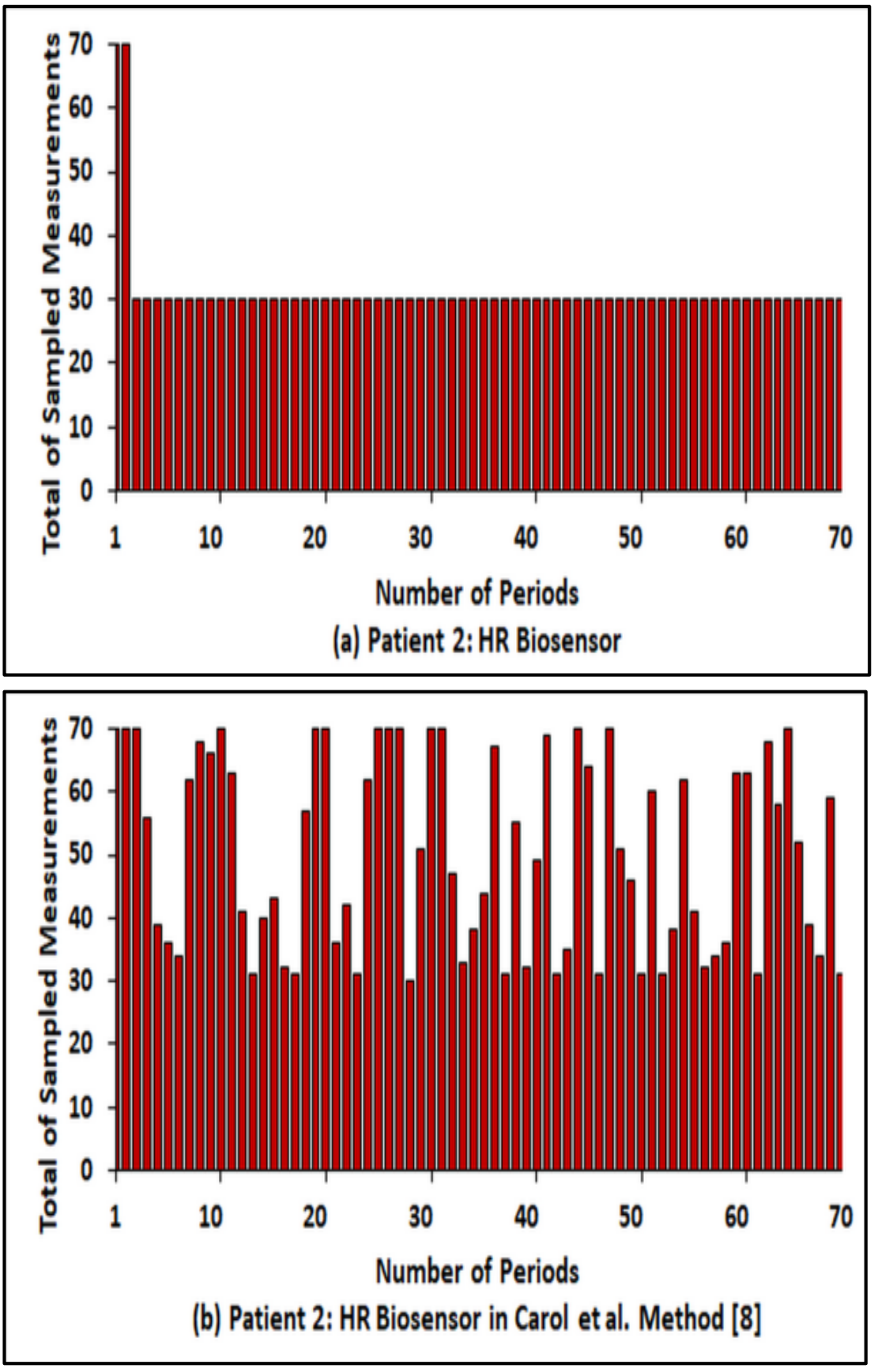


Figure 4.5 sampling rate adaptation (a,b) for patient 2.

4.3.2. Remaining Energy

The energy saving is an important factor that should be considered during designing the protocols in the biosensor network of IoHT. Figures 4.6 and 4.7 refer to the comparison of remaining energy between the proposed EMASA approach and the Carol's method for patient 1 and patient 2 respectively. The EMASA approach utilizes the same energy consumption model that used by Carol's method. It is assumed that the energy unit is equal to the 152 of Joules. The computation task takes 24 Joules, the task of sensing takes 6 Joules, the task of receiving takes 62 Joules, and the sending task consumes 60 Joules . In this work , it is supposed in Carol's method and the proposed EMASA that each sensed reading consumes energy of 0.6 units to send it to the Edge gateway. The sensing task takes the energy of 0.04 units, the computation task takes 0.16 units of energy, and the sending task consumes 0.4 energy units. Each biosensor node is initialized with 4000 units of energy.

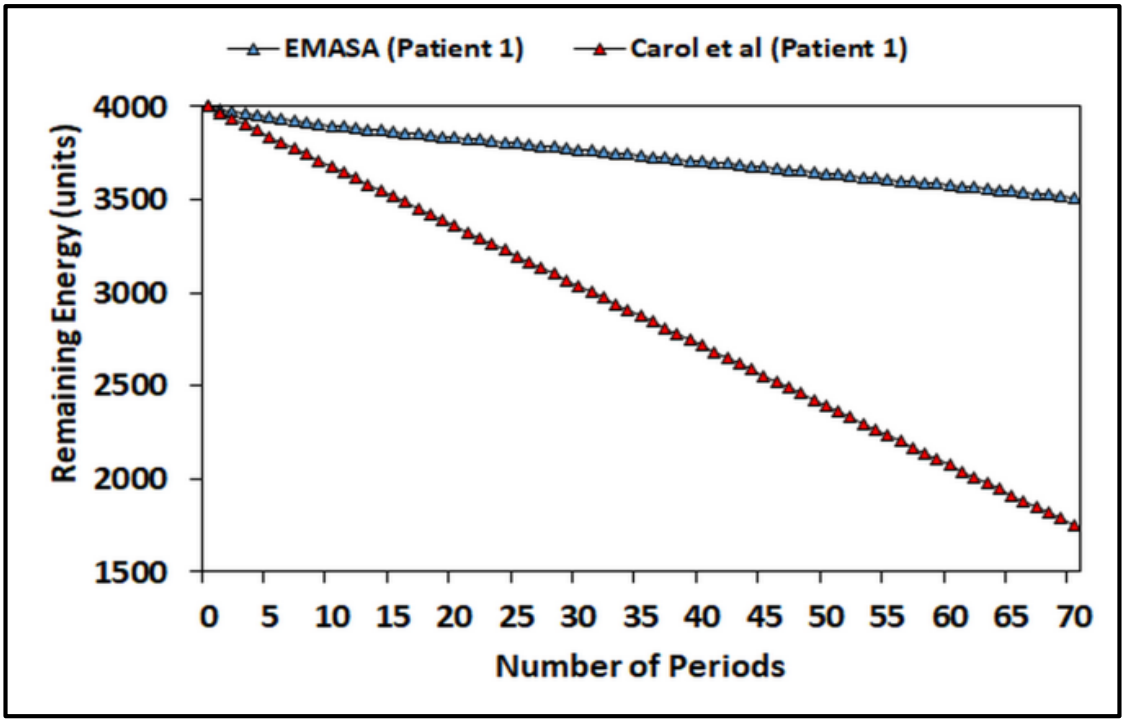


Figure 4.6 Remaining Energy for patient 1.

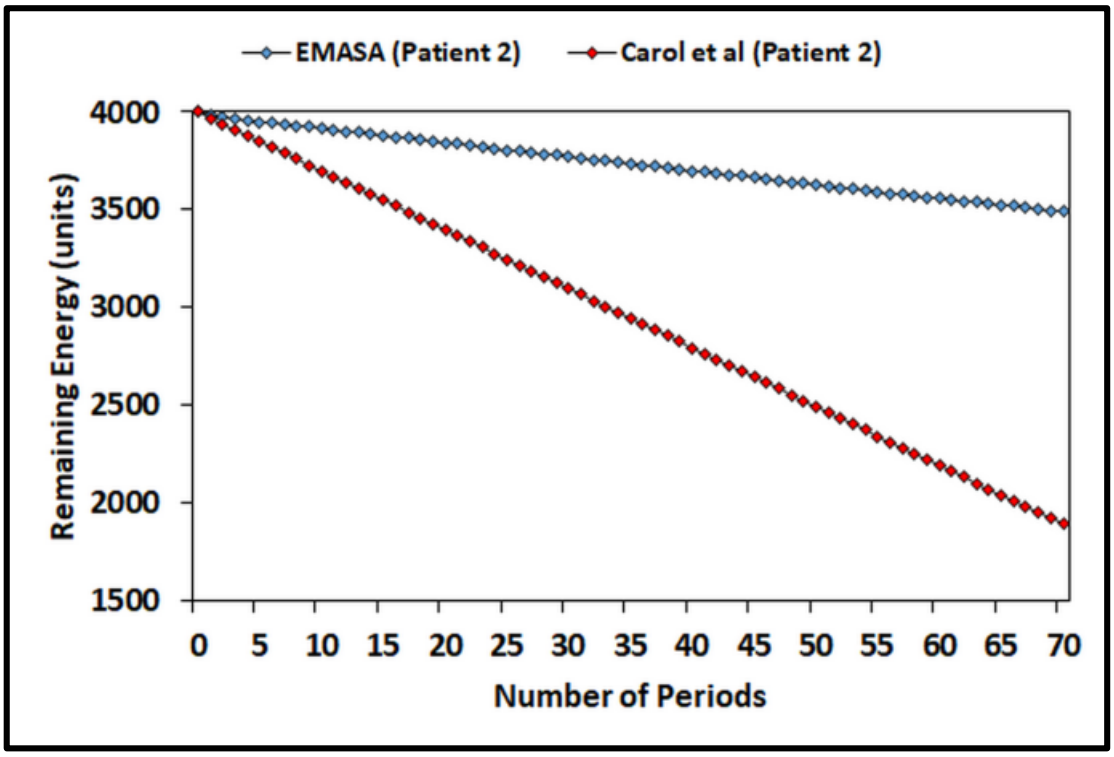


Figure 4.7 Remaining Energy for patient 2.

In Figure 4.6 the EMASA approach consumes less energy compared with Carol's method. The EMASA consumes 12.74% of the energy while Carol's method consumes 52.78% of the energy. It can be seen that the EMASA approach saves 78.35% of the energy of the HR biosensor compared to Carol's method. In Figure 4.7 the EMASA consumes 12.16% of the energy while Carol's method consumes 56.16% of the energy. It can be observed that the EMASA approach saves 75.86% of the energy of the HR biosensor compared to Carol's method. However, the EMASA approach reduces the consumed energy due to the energy-efficient sampling approach adapted with the temporal correlation of sensed readings in the two periods inside each biosensor node. This approach participates in removing the redundant data and sending the necessary ones to the Edge gateway.

4.3.3. Data Reduction

This experiment studies the percentage of data reduction by the proposed EMASA approach using the adaptive sampling and emergency detection algorithms at the biosensor nodes and over 70 periods. Figure 4.8 illustrates the data reduction at the biosensor nodes for patient in comparison with Carol's method. It can be seen that the proposed EMASA approach reduced the data from 93.5% up to 99% in comparison with Carol's method. The EMASA approach decreased the sensed data as an average of all biosensor nodes about 98% whilst Carol's method decreased the data by about 47%. Therefore, EMASA outperforms Carol's method in terms of data reduction.

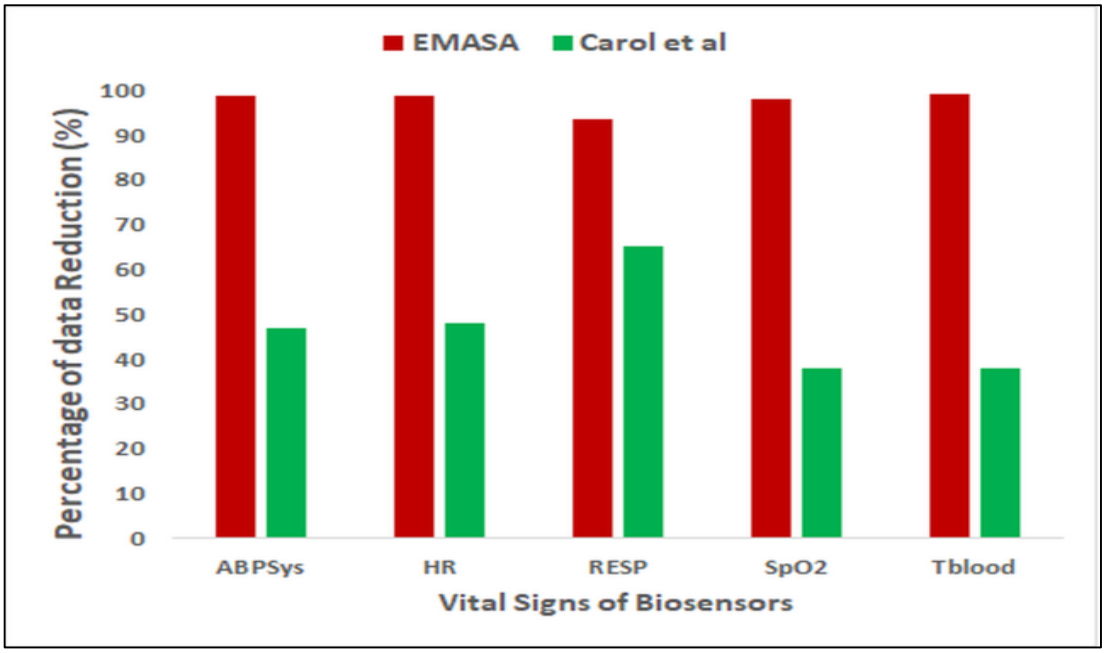
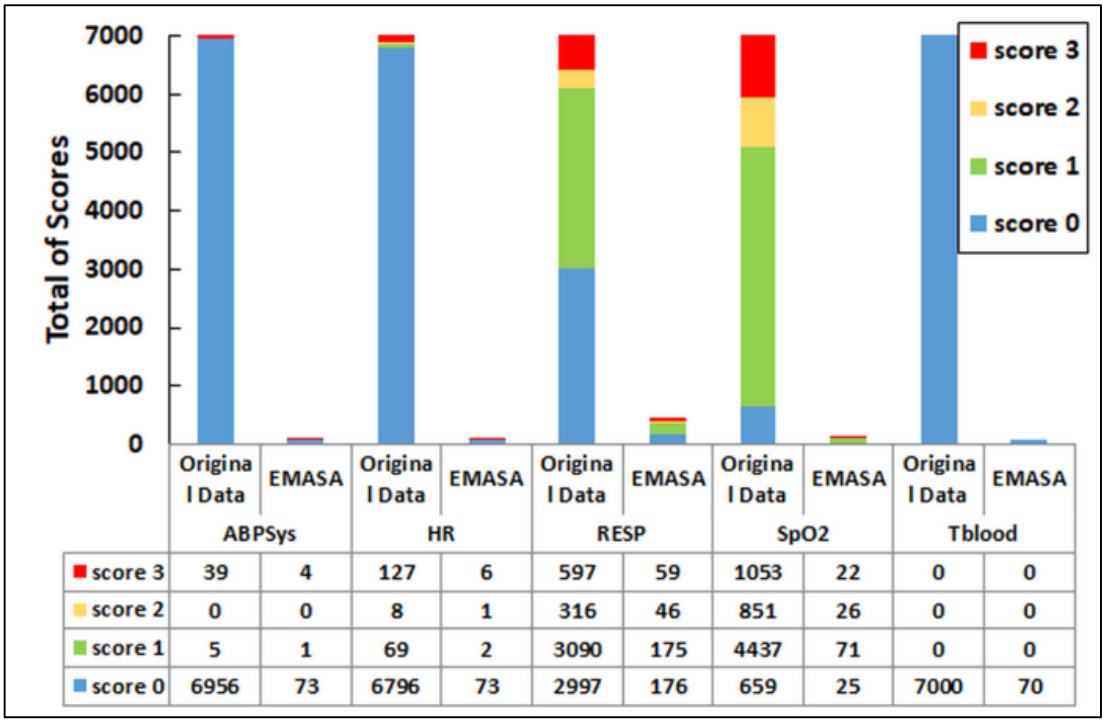


Figure 4.8 Data Reduction for patient .

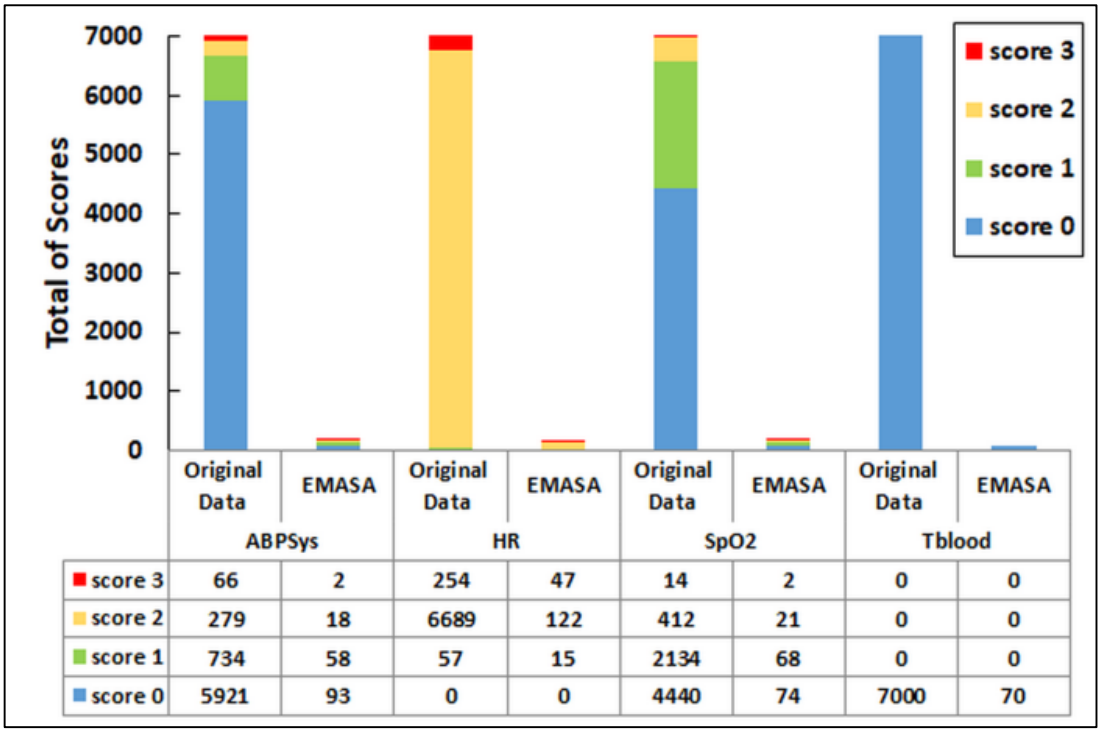
4.3.4. Integrity of Data

This experiment studies the impact of the EMASA approach on the integrity of data over 70 periods. Figures 4.9 and 4.10 present data integrity for both patients 1 and 2 respectively.



	ABPSys		HR		RESP		SpO2		Tblood	
	Original Data	EMASA	Original Data	EMASA	Original Data	EMASA	Original Data	EMASA	Original Data	EMASA
score 3	39	4	127	6	597	59	1053	22	0	0
score 2	0	0	8	1	316	46	851	26	0	0
score 1	5	1	69	2	3090	175	4437	71	0	0
score 0	6956	73	6796	73	2997	176	659	25	7000	70

Figure 4.9 Data Integrity for patient 1



	ABPSys		HR		SpO2		Tblood	
	Original Data	EMASA	Original Data	EMASA	Original Data	EMASA	Original Data	EMASA
score 3	66	2	254	47	14	2	0	0
score 2	279	18	6689	122	412	21	0	0
score 1	734	58	57	15	2134	68	0	0
score 0	5921	93	0	0	4440	74	7000	70

Figure 4.10 Data Integrity for patient 2.

The figures introduce the distribution of the reading scores of original and sensed data records by EMASA for the biosensor nodes for both patient 1 and patient 2. The EMASA ensures a good level of data integrity of

gathered readings at the Edge gateway where it prevents losing scores after implementing the adaptive sampling and emergency detection. Despite the EMASA reduces the data readings to 98.8% in the HR biosensor node compared to the original data (see Figure 4.9), it maintains nearly similarly scores' distributions. This is the same for other biosensor nodes

4.3.5. Aggregated Scores with Decision Making

This experiment shows aggregated scores and the decision that is taken by the EMASA approach using the SVM model at the Edge gateway over 70 periods. Figures 4.11 and 4.12 present the aggregated scores for both patients 1 and 2 respectively .

The aggregated score is computed by summation of the updated scores of all biosensor nodes. The larger value of the aggregated score refers to the higher level of risk of the status of the patient.

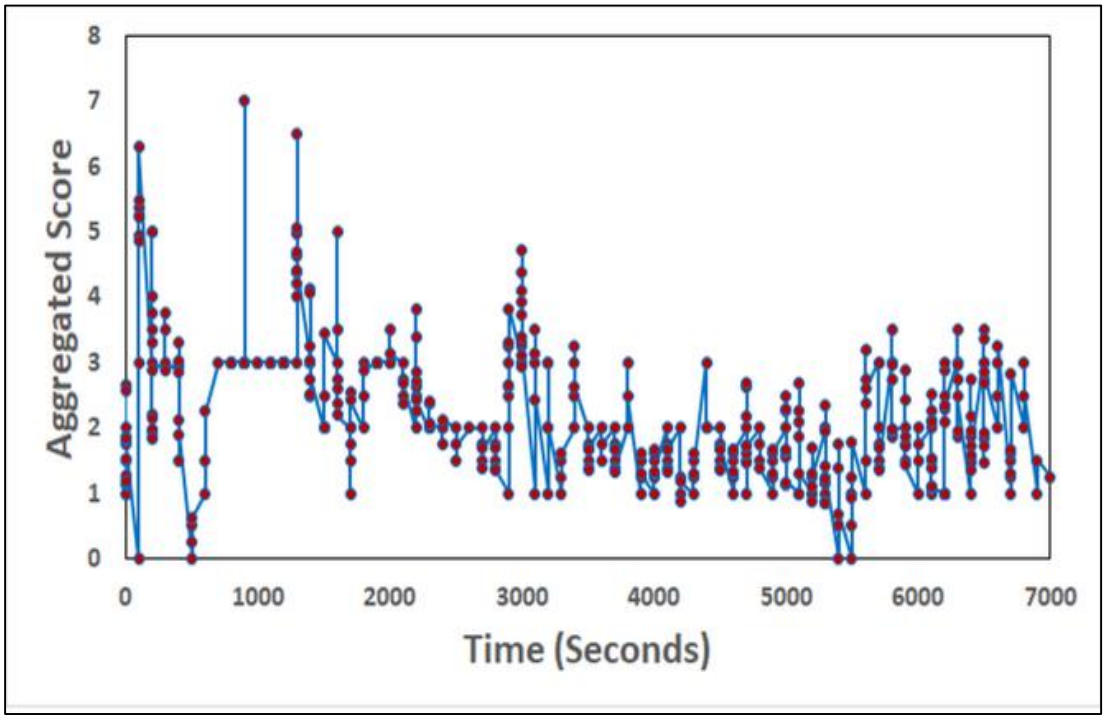


Figure 4.11 Aggregated scores for patient 1

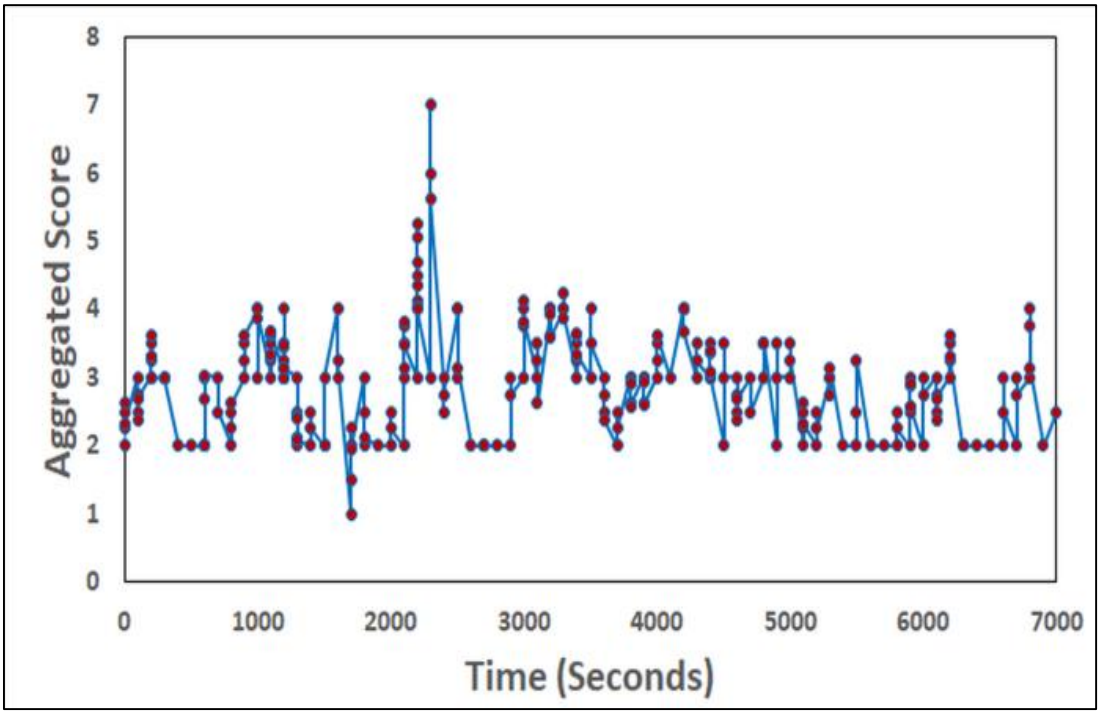


Figure 4.12 Aggregated scores for patient 2.

Figures 4.13 and 4.14 show the decision making for both patients 1 and 2 respectively. In each period, the Edge gateway will take the appropriate decision whenever it receives a crucial score based on the status of the patient.

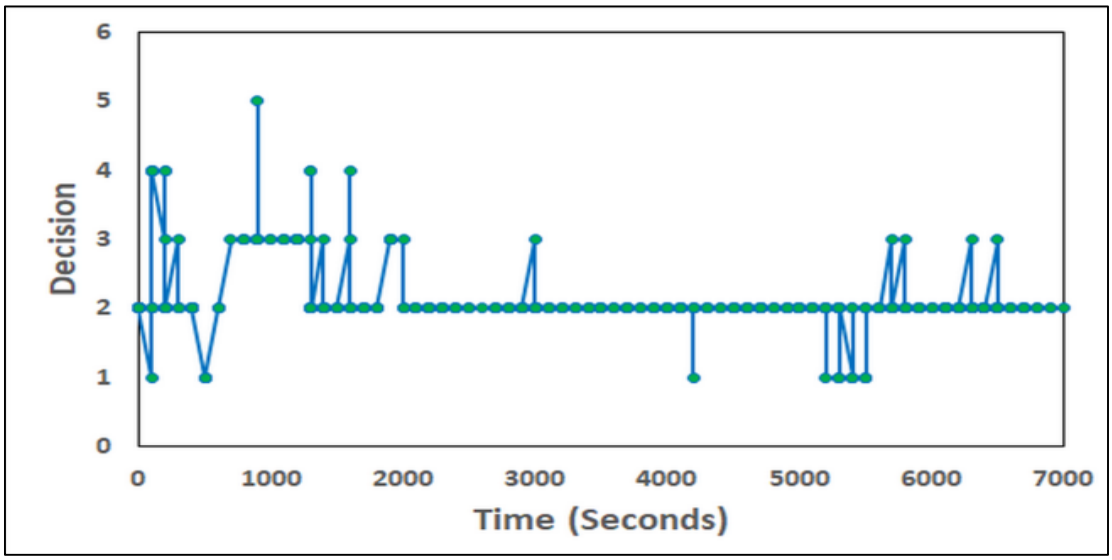


Figure 4.13 Decision making for patient 1.

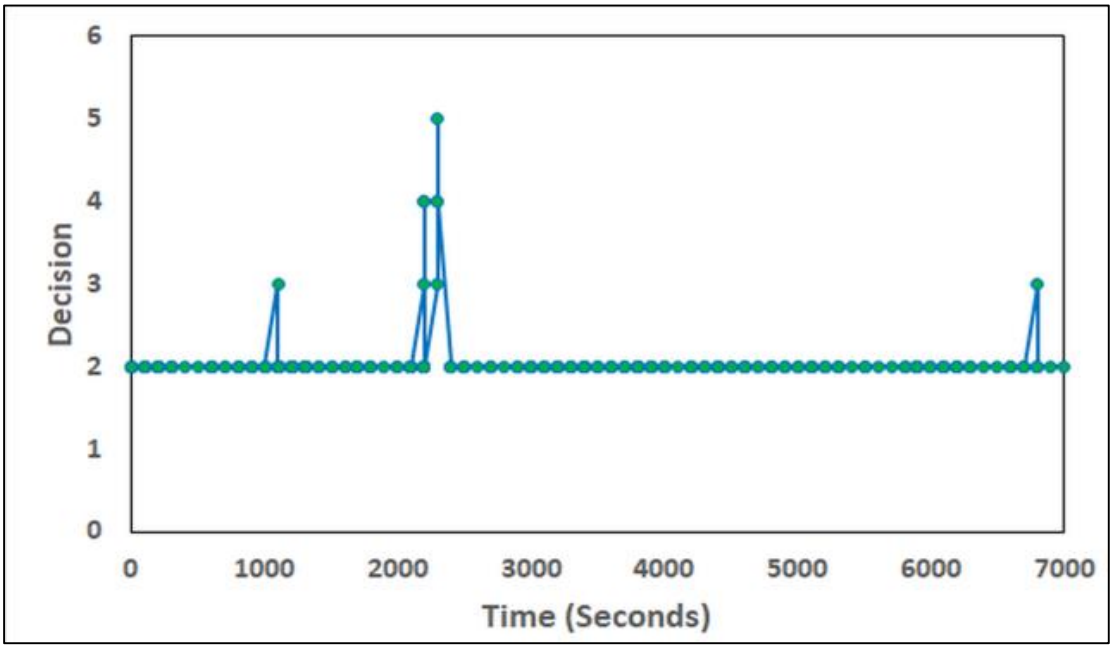


Figure 4.14 Decision making for patient 2.

The decision will be according to the aggregated score, and the output is based on the chart of clinical response (see Figure 4.14). The decisions are predicted using the SVM model. This model is trained based on the updated scores, aggregated scores, and the decision based on Table 3 that inspired from the chart in table 2 .This Table explains the decision's number, the range of aggregated scores for each decision, and the level of clinical risk. The decisions are located in the range from 1 to 5.

4.3.6. SVM Model Evaluation and Analysis

This section focuses on the SVM model evaluation that used by the Edge gateway to provide the decisions remotely and continuously during monitoring the patient. Figure 4.15 shows the performance metrics for different kernel functions used by SVM model.

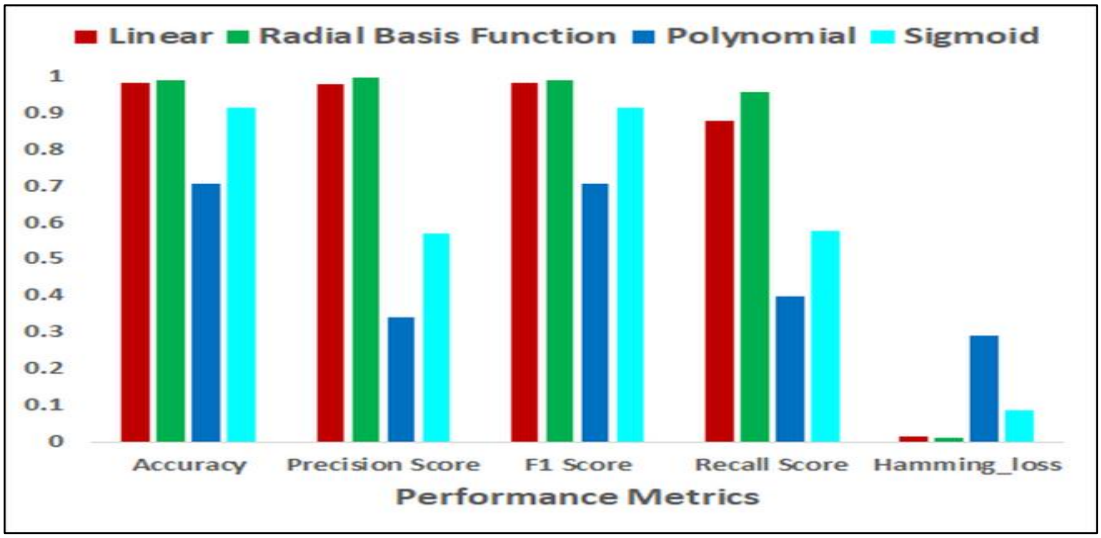


Figure 4.15 The performance metrics for different kernel functions used by SVM model.

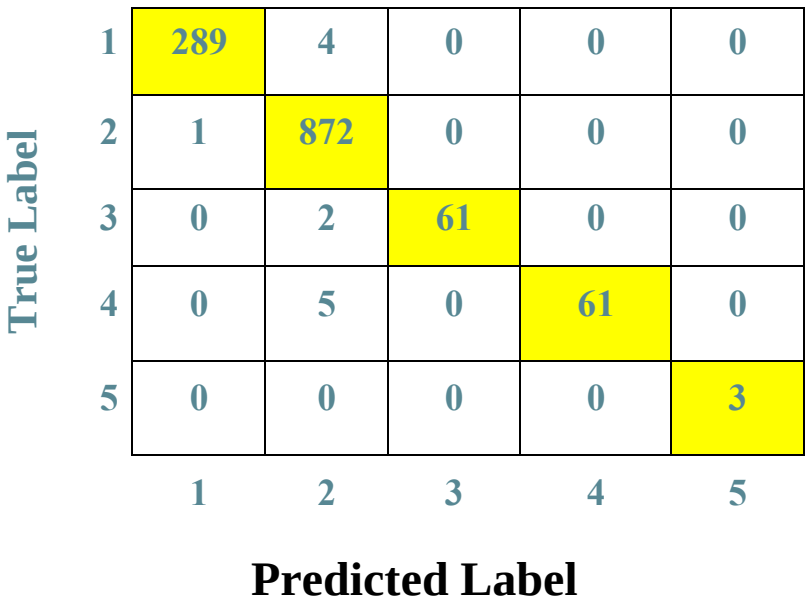
The results in Figure 4.15 shows that the SVM model with Radial Basis Function (RBF) introduces better results in comparison with other kernel functions. These performance metrics are calculated according to the sklearn.metrics module that invited by the Python language whereby k-fold cross-validation was carried out. In RBF, the parameters random state, gamma, and C are fixed to 1, 0.5, and 2.2 respectively. Hence, this section focuses on the SVM model with RBF kernel. The other performance metrics like the classification report and the confusion matrix can be presented to assess the decision maker (classification model) that proposed at the Edge gateway using sklearn.metrics module. Table 5 shows the classification report for SVM model-based RBF kernel.

Table 4.2 the classification report for SVM model-based RBF.

Class	Precision	Recall	F1-Score	Support
1	1.00	0.99	0.99	293
2	0.99	1.00	0.99	873
3	1.00	0.89	0.94	18
4	1.00	0.92	0.96	66
5	1.00	1.00	1.00	3
Accuracy	0.99			1253
Macro avg	1.00	0.96	0.98	1253
Weighted avg	0.99	0.99	0.99	1253

Figure 4.16 presents the confusion matrix of the SVM model that used by EMASA approach as a decision maker at the Edge gateway for monitoring the patient remotely.

Table 4.3 the confusion matrix of the SVM model.



4.4 Summary

In this chapter, the simulation results of the EASeT technique that implemented at the biosensor node using different performance metrics such as sampling rate adaptation, data reduction, energy consumption, and data integrity. Then, the results of EMASA approach have been introduced. All required experiments for the purpose of this chapter have been exposed thoroughly supported with demonstrating Figures that gave the way to support full understanding for the purpose of the EMASA.

5.1. Conclusions

- An energy-efficient Multisensor Adaptive Sensing and Aggregation (EMASA) approach is proposed for patient monitoring in Edge computing based IoHT Networks. The EMASA is applied on two levels in the Edge-based on IoHT network: biosensors and the Edge gateway.
- An integrated local emergency discovery with sampling rate adaptation is implemented at the biosensor level to remove the redundant data before sending it to the Edge gateway.
- The biosensor achieves the emergency detection and sampling rate adaptation using proposed EASeT technique to reduce the transmitted data to Edge gateway and detect the local risk of the patient.
- The Edge gateway aggregates the readings of the biosensors and then provides an accurate decision according to the situation of the patient using a machine learning-based SVM model.
- The performance evaluation shows that EMASA approach produced a powerful result in terms of sent data, energy consumption, and data integrity compared with other methods. It maintains nearly similarly scores' distributions and provides accurate decisions according to the status of the patient.
- The SVM model evaluation that used by the Edge gateway to provide the decisions remotely and continuously during monitoring the patient show competitive results during decision making.

5.2. Future Works

- We plan to implement the compression approaches at the biosensors to compress the readings without losing their meaning at the Edge.
- We attempt to adjust our approach to take into account different biomedical data like the video for operations, images for organs, etc.
- Real experimentation using real biosensor and gateway to implement the proposed approach is one of our focuses in future.

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الملخص

أدى التطور السريع في إنترنت الأشياء (IoT) إلى زيادة التقدم في صناعة الرعاية الصحية. أدى التطور في النظام الأساسي للأجهزة ، بالإضافة إلى البرنامج الأساسي ، إلى ظهور إنترنت أشياء الرعاية الصحية (IoHT). تم زيادة الطلب على أنظمة المراقبة المستمرة للرعاية الصحية عن بعد باستخدام أجهزة استشعار حيوية ذات موارد محدودة. ستعمل أجهزة الاستشعار الحيوية هذه على زيادة البيانات المجمعة والمرسلة عبر شبكة IoHT. لذلك ، فإن تقليل البيانات التي تم جمعها واتخاذ قرار في بوابة Edge يمكن أن يوفر طاقة أجهزة الاستشعار الحيوية وينتج استجابة سريعة للطاقم الطبي.

تقترح هذه الرسالة أخذ عينات متكيفة مع أجهزة الاستشعار المتعددة وتقييمها لمراقبة المريض في تطبيقات الرعاية الصحية المتصلة. يتم تنفيذه على مستويين في شبكة IoHT القائمة على Edge: المستشعرات الحيوية وبوابة Edge. في أجهزة الاستشعار ، لإزالة البيانات الزائدة عن الحاجة أثناء مراقبة حالة المرضى. تعمل في طريق الجولات. هناك فترتان في الجولة. يعد اكتشاف الطوارئ وتكييف معدل أخذ العينات لكل جهاز استشعار حيوي خطوتين رئيسيتين في هذا المستوى. يتم تنفيذ SVM (Support Vector Machine) القائم على التعلم الآلي على مستوى البوابة. يتم تدريب نموذج SVM بناءً على البيانات التي تم جمعها من أجهزة الاستشعار المتعددة المنتشرة على جسم المريض. يمكن لهذا النموذج المدرب اتخاذ قرار مناسب بشأن حالة المريض الخاضع للمراقبة.

لقد أنجزنا العديد من التجارب بناءً على بيانات مستشعرة حقيقية من أجهزة الاستشعار الحيوية للمرضى. توضح النتائج أن الطريقة المقترحة تقلل البيانات المرسلة من 93.5٪ إلى 99٪ وتوفر 78.35٪ من الطاقة مقارنة بطريقة كارول. إنها تحافظ على تمثيل جيد للنتائج الكاملة في بوابة Edge وتوفر قرارات دقيقة وفقًا لحالة المريض.

وزارة التعليم العالي و البحث العلمي
جامعة بابل كلية العلوم للبنات
قسم علوم الحاسوب

اخذ عينات وتقييم متاقلم متعدد المستشعرات واعي للطاقة لمراقبة المريض بالاعتماد على IoHT

رسالة مقدمة الى مجلس كلية العلوم للبنات في جامعة بابل وهي جزء من متطلبات الحصول على درجة الماجستير في علوم الحاسبات

مقدمة من قبل
دعاء عبد الحسين ناصر

باشراف

الاستاذ الدكتور
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