FAULT-TOLERANT MULTIMODAL SAFETY-RELATED MEDICAL SYSTEMS

Thesis Submitted in partial fulfilment
of the requirements for the degree of

Doctor of Philosophy in Electronics and Communication Engineering

by

Lakkamraju Venkata Rama Prasada Raju
201150821
Prasadaraju.Lvr@research.iiit.ac.in

International Institute of Information Technology, Hyderabad
(Deemed to be University)
Hyderabad-500 032, INDIA
SEPTEMBER 2023.

International Institute of Information Technology
Hyderabad, India

CERTIFICATE

It is certified that the work contained in this thesis, titled **"*Fault-Tolerant Multimodal Safety-Related Medical Systems*"** by L.V.R. Prasada Raju, has been carried out under my supervision and is not submitted elsewhere for a degree.

_____ _____

Date Advisor: Dr. Shubhajit Roy Chowdhury

INTERNATIONAL INSTITUTE OF INFORMATION TECHNOLOGY (IIIT-H),
(DEEMED UNIVERSITY)

"FAULT-TOLERANT MULTIMODAL SAFETY-RELATED MEDICAL SYSTEMS"

ABSTRACT

The safety improvements in the medical systems or devices, specifically non-invasive patient monitoring systems (PMS) and point-of-care (POC) devices of human health monitoring (HHMS) systems, are in great need to perform precise measurements of vital parameters with uninterrupted continuous monitoring for diagnosis of significant human health ailments. During critical or non-critical nursing times, frequent monitoring of short and long-duration measures of vital parameters (like ECG, EEG, Respiratory, SpO2, Blood-pressure, Temperature, etc.) and non-vital parameters (like Glucose levels, Hemoglobin, Urea in blood, etc.) will allow for better nursing and early detection of diseases like cardiovascular diseases, respiratory diseases, liver dysfunction, diabetes, renal diseases, and other psychological disorders. A non-invasive medical instrumentation system for accomplishing these tasks must meet several criteria like accuracy and precision of the measurement, reduction of false alarms, effective detection of faults, and fault tolerance to systemic or random failures with an uninterrupted performance during nursing times.

Many research groups have made many efforts worldwide to make strategies and guidelines and standardize the procedures for medical systems based on safety design approaches to raise alerts for any deviance during non-invasive monitoring of health parameters. In addition, health monitoring instruments should be portable, low-cost, and reliable over time. Many modes of diagnosis and related instrument maintenance procedures satisfy these criteria. However, most of them are still in the improvement stage for developing resilient instruments for integrating with critical auto-robotic surgery instruments with minimal human intervention.

Several approaches have been proposed, out of which safety-related design approaches like using 2oo2, 2oo3, 1oo2, etc., along with AI-based data analytics, have the advantage of meeting these rigorous demands in fundamental safety improvements of Medical Systems. Based on the safety-related design 2oo2 concept, a configurable system prototype of the cardiac health monitoring system (CHMS) is developed and evaluated to meet the set objectives, such as fault

detection effectiveness and fault tolerance with improved safety configurability. This configurable system uses various sensors to collect the bio-medical data in parallel. Primarily, three diverse sensors are used non-invasively in sensing the bio-signals in different forms like electric potential, light, and sound signals for computations. These diverse sensors are used to detect biomedical signals to obtain data from electrocardiogram (ECG), Photo-plethysmogram (PPG), and Phonocardiogram (PCG). Therefore, the accuracy of the vital estimates and the fundamental safety improvements were evaluated using this multimodal system with AI-based fault detection and predictive maintenance techniques.

Traditional statistical and AI-based techniques have acquired authentic measurements of human health parameters from diverse signals received simultaneously from various sensing circuits like PPG/ECG/EEG. Secondly, these bio-signals are calibrated independently with known algorithms in diverse. Finally, these obtained parameters, along with the built-in-test (BIT) system for health signals, are processed with implemented safety functions, and the algorithms to generate the correct human health parameters and prognosticate abnormalities of human health 200 patients were available for instrument evaluation trials for HR parameter monitoring and tested after taking informed consent. A MATLAB-based CHMS tool is developed for configurable and then implemented on a field-programmable gate array (FPGA) to minimize the designed circuitry with improved resiliency of the instrument system. The CHMS has been configured to 2oo2 with the selected HR parameter to estimate the system's availability and health. The collected HR output was subjected to data analytics against individually collected data. We found a significant reduction in the generation of unimportant alarms and increased uninterruptable System availability by 45% to 55%, along with normal and abnormal artifact data. The measured normal artifacts are more than 99% accurate and are used for prognosis. The abnormal data is used for edge-AI-based analytics to infer the system's health for prescriptive maintenance. An experimental study has been carried out to effectively segregate normal and abnormal signals in 2oo2 and 2oo3 configurations. A detailed analysis is carried out in various sensor configurations as proposed. Similarly, in the 2oo3 configuration, we significantly improved the system's availability from 55% to 95% by eliminating spurious alarms with reduced downtime and improved accurate data vital parameters.

Further, a reliability assessment is performed on CHMS on identified parameters, such as measuring Availability, Mean-time-between-failure (MTBF), Mean-time-to-failure (MTTF),

Repeatability and Reproducibility. The higher the MTBF number, the higher the product's reliability. Measured the MTBF, in terms of its recovery time when a failure does occur. The experimental assessments performed for the estimation of reliability improvements have been verified in comparison with the existing 1oo1 systems. Overall Availability of the system improved by 45% to 55% in the 2oo2 configuration, whereas 55% to 85% improved in -2oo3 configured systems with respect to 1oo1 systems. The assessment of MTBF for the 2oo3 system is 28.40 min, and for the 2oo2 system is approx. 24.60 min is recorded. Thus, a significant improvement was noticed in reliability when compared to 1oo1 systems with MTBF of average approx. 13 min. The repeatability and reproducibility parameters are measured for the CHMS; in the 2oo2 configuration, the repeatability is assessed as 0.79, whereas for 2oo3, it is 0.1414, which shows very less variance in the system repeatability and reproducibility parameters.

In this thesis, an attempt has been made to use safety-related architectures to build CHMS and evaluated with implemented functions like fault detection and identification logic, correlation coefficient-based safety function, and fault-tolerant safe degradation switching mechanism for accurate measurements. Furthermore, different correlative safe functions and reliability assessments were performed, such as system-level MTBF, MTTF, Availability, repeatability and reproducibility. Moreover, predictive or prescriptive maintenance methods have been adopted and evaluated to identify a safe design approach appropriate for measuring authentic data and improving system health.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Dedicated to Almighty

ACKNOWLEDGEMENTS

I thank my advisor, Dr. Shubhajit Roy Chowdhury, for all his support throughout my research and thesis work.

I thank my advisor for showing continuous belief in me even though I was employed in the IT services industry performing a full-time job in parallel. His timely advice with kindness, meticulous scrutiny, and scientific approach has helped me accomplish this research.

I profusely thank all the staff of CVEST and the administration staff, specifically Kishore.Y, Prathima.M, and Pushpalatha.B for their kind help and cooperation throughout my Ph.D. journey.

It is my privilege to thank my parents, my sister, and all my best REC MSc[Tech] classmates for their constant motivation and support throughout my research.

I owe a deep gratitude to all of my teachers, mentors, friends, colleagues, and specifically Madhubabu A, without whose support I may not have been able to conduct this research.

Chapter 1. Introduction

Engineering biomedical systems using sensing and computational elements to estimate accurate pathophysiological parameters is one of the most challenging and fundamental problems in medical science [1], [2], [3]. Therefore, engineering electronic medical systems requires following system engineering principles and continuous improvement in innovative design concepts for its implementation in medical systems resilience to overcome the systemic and random failures of the system and enhance the accurate measure of the pathophysiological parameters of human life beings.

Advanced intelligent medical systems engineering for safety-critical medical applications requires several dependable features, such as the system's functional safety, availability, and reliability in signal processing algorithms [4]. Furthermore, advancements in high-performance electronics and sensors have become affordable and, thus, increased the usage of these intelligent medical systems in clinical environments, such as in intensive care units(ICU) or operating labs [5], by performing critical patient treatments like robotic surgeries & medication supervisory by continuous monitoring of the patient's health parameters[6], [7], [8], [9], [10], [11]. However, these smart, intelligent multimodal computational electronic system, along with system portability, come with a substantial increase in system complexity and brings in significant challenges like functional safety [12], reliability of measurements[13], and Patient Safety[14], [15], [16]. Moreover, this type of safety-critical smart medical monitoring system is often subject to an insignificant number of failures with potentially catastrophic impacts on patients[17], [18], [19], [20].

Medical systems are divided broadly into in vivo and in vitro. This thesis focuses on vitro-based non-invasive patient monitoring medical (PMS) systems, where a measurement is performed outside the human body. Nowadays, medical practitioners and healthcare providers depend on medical monitoring systems to safely perform disease diagnoses in various situations and clinical environments. However, medical systems such as patient monitoring systems or Point-of-Care (POC) medical devices have become more portable and advanced and have increased in complexity[21]. As a result, their response to user inputs, environmental inputs, and component failures is not as predictable[22]. Therefore, a systematic approach to system safety is

essential to developing fault-tolerant multimodal safety-related medical systems successfully and cost-effectively.

1.1 Human Health Monitoring Systems

A human health monitoring system[HHMS] is a device or system that helps nursing staff or healthcare providers monitor the vital and non-vital physiological signals and parameters of the patient's health. These monitoring systems are used to observe and measure a patient's health parameters such as heart rate, respiratory rate, blood oxygen saturation, temperature, and many other parameters for a critically ill or diseased patient. Such accurate and instantaneous information helps make crucial decisions for effective patient care and better nursing.

1.1.1 Importance of Human Health Monitoring Systems

Human health monitoring systems or Point-of-care devices are central nowadays. It provides warning signs of early or dangerous deterioration of a patient's health so practitioners or nursing staff can make the required changes in their treatment based on the severity[23]. The real-time data support doctors in prioritizing their patients and providing urgent care to those who need the most danger, thereby saving valuable lives.

Human health monitoring aims to have a quantitative assessment of the vital physiological variables of the patients during life-threatening periods of their biological organ functions. Moreover, it is required to know their actual value or trend of change for research and diagnostic purposes.

1.1.2 Types of Healthcare Monitoring Systems

Human healthcare monitoring systems are categorized broadly into two main types: patient monitoring systems or bedside patient monitoring systems and remote patient monitoring systems or point-of-care medical devices.

1.1.2.1 Bedside patient monitoring systems(BPMS)

Bedside patient monitoring systems can also be mentioned as hospital patient monitoring systems. These are used within hospitals to monitor patients' vitals and ICU settings. In addition, bedside patient monitoring systems are required for patients in the trauma and long-term patient

monitoring for all vital signs to prevent complications in post-surgery patients and ensure complete recovery[24][25][26][27].

1.1.2.2 Remote patient monitoring systems(RPMS)

A remote patient monitoring system(RPMS) monitors patients outside the hospital environment, i.e., remotely[28]. It can also be called a home patient monitoring system. This system enables medical practitioners to monitor a patient's health remotely. The system provides seamless continuous data, which helps medical practitioners monitor real-time variations in a patient's health data from a distance and use it in planning for better nursing for the patient [29][30][31][32][33].

1.1.2.3 Point-of-Care Diagnostic Systems

Point-of-care diagnostic devices[25] are portable devices used to obtain diagnostic results in a short duration at or near the patient's premises. The College of American Pathologists (CAP) describes these Point-of-care Test (POCT) devices as ‘testing that does not require permanent dedicated space and it refers to those analytical patient-testing activities provided within the institution, but performed outside the physical facilities of the clinical laboratories [240]. These gadgets are used in doctors' offices, hospitals, and patient's homes. These POC diagnostic devices provide quick feedback on many medical tests and are repetitive in short durations[34][35][36][37].

1.1.3 Safety aspects in Health Monitoring Systems

Safety is one of the essential considerations while designing and developing next-generation medical systems[38][39], as these systems are becoming more complex. Ensuring patients and healthcare providers' safe usage of medical monitoring systems solutions is a significant challenge for system designers and manufacturers to avoid critical situations. However, there are many methods and approaches to addressing such challenges[12],[13], [14],[15] [16].

With recent advancements in information technology and the availability of information, System Design engineers new to the medical field are sometimes surprised to discover the lengths to which they must go before their medical devices can be considered safe for use. However, the product development life cycle (PDLC) generally takes five to ten times more effort to develop a safe device and comply with regulations than to develop a laboratory

prototype. Thus, a device can only be considered safe after undergoing extensive tests that prove its safety. So, the safety discussion starts by devising the proper evaluation tests that provide that proof.

The principles of Safety engineering emphasize mainly three aspects that are particularly important in making electronic instrumentation[40][41][42] safe, which they can apply:

1. Hardware: Medical hardware uses a functional safety approach where two independent failures are not allowed to harm the patient.
2. Software: There are rules for designing software so that the chances of harm arising from bugs are acceptably low.
3. User Interface: The design should employ usability rules that make the man-machine interface safe.

However, a few aspects, like the usage of materials and equipment, make procedures follow, ensuring enough to guarantee that it is safe[43]. However, industry standards are critical and cannot cover all risks. So, the designers must make up the right design strategies[44][45] for the area's standards do not covered by conducting a comprehensive risk analysis[46][47].

Developing safe medical devices deep down in design to identify risks and establish measures that give the confidence to say the risks are acceptable. First, designers must judge the severity level of potential harm and the probability that the harm occurs. Once developers have identified the unacceptable risks, their next step is to define safety measures to mitigate them. Fortunately, some standards guide safety. One of the primary medical-device safety standards is IEC 60601-1 – Medical electrical equipment – Part 1: General requirements for basic safety and essential performance[48].

1.1.3.1 Safety Aspect of Hardware

One of the principles of IEC 60601-1 is that a medical device must be safe in the case of a single fault. It defines a single fault as a failure of a safety system. Thus, one facet of designing a safety device is to imagine how the first failure in a safety system could endanger the patient and then implement a safety system that still makes the device safe even in the event of a first failure [49] [50].

Though medical devices must-have designs that prevent two independent hardware failures from harming a patient, elevator designs must be safe in the event of three independent failures. All in all, the possibility of multiple lost lives brings stiffer safety requirements.

Another important safety factor is that the safety system has its reliability level[51][52][53]. A designer must establish what this level is. One approach to make safety systems reliable is to use two redundant safety systems or one system that is tested periodically to see if it is still functioning. The primary approach is to go through every device component and determine what happens if it fails. Each possible failure is acceptable if it is obvious, and an operator can stop operations before the device can harm someone[54][55]. So, the failures can be either systematic or random.

1.1.3.1.1 Systematic failures

Systematic type failures are built-in design flaws, such as:

- Errors in the PCB layout, components used outside their specification, or unanticipated environmental conditions
- All software bugs are systematic failures and not random software failures, but the effect of software failures might be random.
- errors in the software specification and errors in the operating system or compiler

A robust development process can prevent systemic problems in both hardware and software.

1.1.3.1.2 Random failures

Random type failures, such as:

- Errors happen even though the design is correct and production is flawless.
- Hardware failures cannot be predicted individually and can only be described statistically[56].

Thus, the general approach to controlling random errors is with redundant features by adding self-testing or a safety system that reacts in the event of a random failure.

To improve the system reliance, the designers typically use redundancy and diversity as safety features[57]. Redundancy duplicates the same feature, while diversity uses two different methods to deliver the same function. Diversity protects against random hardware errors as well as against some systematic failures. Redundancy, on the other hand, protects only against

random hardware failures. One of the questions that designers must decide is how much protection they must build against random hardware failures. The solution depends on such factors as whether a first failure is a hazard and whether designers should assume there is a possibility of a second, third, or even more numerous failures.

The main logic here is that hazards potentially able to kill multiple people at one strike demand more attention. The potential for harm will guide how many independent failures designers must consider in the device's lifetime. The potential for harm also determines the amount of redundant/diverse safety systems necessary. Normally, medical devices kill one person, so designers must consider a maximum of two independent failures. In general, designers must consider the possibility of ever-more unlikely events, the higher the risk of harm.

The IEC 60601-1 standard specifies that a combination of two independent failures should not be life-threatening for electrical medical devices. This mandate expresses the concept of the single fault condition for medical devices. The principle is that a first failure should not cause a hazard. If the first failure is evident to the operator, the operator stops using it and has it repaired. If the first failure cannot be detected, the designers must assume that a second failure will arise sometime later. They must also arrange the design so a combination of the first and second failures will not cause a hazard. Unfortunately, the term "single-fault condition" can be misleading in the context of medical safety standards. It can suggest that designers only assume that the device experiences only one failure, which is incorrect. Usually, there is a period after the first failure where the combination of a first and second failure is not allowed to be a hazard. Here the designers, need to have an in-depth understanding of the parameters like Mean-Time-Between-Failure (MTBF), Mean-Time-To-Failure (MTTF) and Mean-Time-To-Repair (MTTR) before going for a risk assessment on each fault condition[48].

The designers must understand the definition of a failure before assessing the parameters like MTBF. To address this ambiguity in failure understanding, one could argue that there are two basic definitions of failure[48]:

1. The termination of the ability of the product as a whole to perform its required function.
2. The termination of the ability of any individual component to perform its required function but not the termination of the ability of the product as a whole to perform.

In reality, there are more than two definitions of failure; in fact, they are infinite, which depend on the type of product, manufacturers quality processes. In general, it is accepted that

electronic systems or components exhibit constant failure rates during their useful operating life. The "normal operating period" or “useful life period" is the stage at which a product or instrument system is in use, then the sources of failures at this stage could include undetectable defects, low design safety factors, higher random stress than expected, human factors, and natural failures.

Instrument reliability ensures that any instrument used for measuring desired parameters gives the same results every time in the same conditions and emphasizes the equipment's ability to function without failure. Reliability describes the ability of a system or component to function under stated conditions for a specified period of time. Reliability is closely related to availability, which has been typically described as the ability of a component or system to function at a specified moment or interval of time [135]. Thus, the higher the MTBF number, the higher the product's reliability. The below equation illustrates this relationship.

$$Reliability = e^{-(Time/MTBF)} \quad (1)$$

Where "$Time$" is a period of time in use

MTTR, or mean time to repair (or recover), is the expected time to recover a system from a failure, this may include the time it takes to diagnose the problem. The below equation shows that MTTR impacts availability and not reliability. The longer the MTTR, the worse off a system is, and in simple terms, if it takes longer to recover a system from a failure, the system is going to have lower availability. So, as the MTBF goes up, availability goes up, and similarly, as the MTTR goes up, availability goes down. The below equation illustrates how both MTBF and MTTR impact the overall availability of a system.

$$Availability = \frac{MTBF}{(MTBF + MTTR)} \quad (2)$$

A risk graph is spelled out in the IEC 61508 standard[58] and categorizes each fault condition with a specific safety integrity level or SIL[58][59]. A progressive procedure for analyzing each hardware failure could be identified as dangerous. Designers usually divide risk consequences into four categories: minor injury, serious injury, several deaths, and many deaths. They further subdivide risks according to the exposure time to the hazard and the possibility of avoiding the hazardous event. Finally, they categorize the probability of the unwanted

occurrence as very small, small, or relatively high. Designers often start the safety analysis with a functional diagram of the product. It is an appropriate starting point because it is possible to build a high degree of safety on the system architecture level [60][61]. Designers typically treat each function as a black box. They then try to determine whether a specific black box is safe or can be made safe by introducing safety systems. When they cannot determine a black box's safety, they open it and go deeper, perhaps down to the level of individual components.

The US FDA maintains a market surveillance system that can give designers a heads-up on potential problem areas in medical devices[62]. The manufacturer must report the details to the FDA if any medical device fails. Alarms are raised if a specific device has a failure rate exceeding a certain threshold[63]. Thus, medical-device engineers can consult this database to see what kinds of failures similar devices are experiencing. Other countries have similar databases of medical device failures. However, their data tends to be less useful than the US because individual countries collect their information. There is no central repository yet for tabulating worldwide results.

1.1.3.2 Safety Aspect of Software

Software for medical devices [64][65][66] has its standard, IEC 62304. It specifies life-cycle requirements for medical software and software development within medical devices[67]. In addition, the standard spells out a risk-based decision model [68] and defines testing requirements [69].

The primary principle for verifying software is to describe the function it is supposed to perform, and then devise a test that verifies the software works as planned. The key lies in devising a specific test to identify all functions. Unfortunately, the medical device industry is not as advanced as it should be when implementing such procedures. In many cases, software descriptions tend to be ambiguous, which causes several harmful side effects, and a statistic that illustrates [70][71] why an accurate description of software functions is essential.

Software-safety analysis frequently employs a so-called V-model analogous to the one widely used for visualizing the progression of system-development tasks. The V-model represents the principle that designers must clearly describe software tasks in several levels of detail[72]. In addition, tests must check that the software delivers its intended functions and identifies any bugs at every level. The software risk model defines three different levels of

safety. Level A software is harmless even if it fails. Level C software if fails, can injure or kill someone. If the software is neither A nor C, it is set to level B by default. Categorizing software into one of the three levels helps determine how much testing is appropriate. Level A software needs a system test. Level B tests must be detailed enough to check individual software modules. Moreover, as expected, most safety-system software in medical devices is at level C, which tests subsets of software code at the unit level.

1.1.3.3 Safety Aspect of Human Interface

It is no secret that operating appliances and instrumentation are getting more complicated. Moreover, complicated medical instrumentation is also prone to operator errors with potentially tragic consequences[73][74]. Complex instrumentation puts a demand on the operator's intellectual ability. However, users are not getting cleverer. Unfortunately, standards for human-factor usability are not well-developed. For example, one such document is IEC 62366 Annexure D 1.4 [48]. It is weak because it only supplies general guidelines about the steps necessary to identify risks of usage problems. It requires designers to analyze how users interact with the device and implement risk-mitigating measures to avoid incorrect usage. It can be expensive for manufacturers to explore and use their equipment's ergonomics. One widely used technique is interviewing the users while they operate the device. The whole set of interactions gets recorded and analyzed. A typical finding in sessions like this is that only about 10% of instrument functions get used daily. The other 90% get used rarely or not at all. However, it is not unusual to find often-used features buried in complicated menu structures with a huge potential for accidentally making an error [74].

However, no standard requires an ergonomic analysis or user studies. Instead, these practices are recommended among firms with experience developing medical equipment.

1.1.4 Common Problems and Challenges in the Design of Health Monitoring Systems

The World Health Organization (WHO) considers the usage of continuous patient monitoring during surgical interventions as "extremely important" for patient safety[75][76][77]. In general [78], a human health monitor electronic instrument measures and displays the vital signs using various sensors. In addition, it enables care providers to take corrective action if a patient's vital signs deviate from their normal range[79]. Thus, these monitoring devices have gained

significant relevance in medical expertise by continuous evolution incorporating great automation and intelligence.

In the design of such intelligent health monitoring systems, the broad common problems are:

- Problem-1: Detection of a great variety of artifacts and interferences.

The varied biological signals detection with appropriate sensory design elements and monitoring techniques [80] is always a problem, which commonly hampers the generation of valuable information and occasionally renders monitoring impossible.

- Problem-2: Elements of hardware and software tools for signal filtering

The quantity and nature of artifacts critically depend on the quality of the monitoring equipment, including hardware and software elements for signal filtering.

- Problem-3: Automatic interpretation of the signal.

The interpretation of the signal and measuring parameter depends on the algorithms and proves to be the most vulnerable in systematic and random failures.

Although HHMS is a complex type of end equipment, there are challenges in the realization of patient monitors. Considering general design aspects, parameters such as power consumption, portability, patient safety, secure delivery of data, integration, reliability and a few main functional features are used to overcome the common cause failures(CCFs)[81] – such as generation of Alarms, processing of Artifacts, Software implementation, Selection of Hardware, consideration of Human interface factors and System factors[82][83].

An ideal health monitoring system should transfer the relevant patient monitoring information as efficiently as possible, prevent false positive alarms, and use technologies designed to improve the problems in patient monitoring.

In this thesis, we have investigated and adopted safety-related design architecture usage in mitigating the reduction of systematic and random failures. Towards this aim, we developed the design concepts in prototyping the cardiac health monitoring system to address some of the above problems and challenges. We implemented these fault-tolerant design concepts of 2oo2 and 2oo3 with safe processing mechanisms by interfacing multimodal sensory such as photo-plethysmogram (PPG), Electrocardiogram (ECG), and Phonocardiogram (PCG). These CHMS experimental research studies were used to improve the effective segregation of authentic artifacts for prognostic health diagnostics and systemic error signals used in processing Artificial Intelligence(AI) based Predictive Maintenance (PdM) for the instrument.

Chapter 2. Research Background and Review of Literature

The growing demand for Safe Medical Monitoring systems in the past couple of decades has increased tremendously [84][85][86]. Therefore, a detailed systematic study was conducted to understand the technological trends in the development of medical health monitoring systems and their inherent failures [87][88][89]. This research's vital emphasis is to improve system operational availability [90] by minimizing the failures using safety-related design architectures [91][92], performing Artificial Intelligence-based PdM[93][94][95], and making authentic artifacts for prognostic health diagnostics [96][97].

2.1 Brief review of the history of Monitoring systems and their development

2.1.1 Patient Monitoring System and its usage studies

Health monitoring systems measure a patient's heart rate and rhythm, blood pressure, breathing rate, blood oxygen saturation, and many other essential and unimportant parameters. It is a common part of treatment for critically ill patients. Electronic monitors are frequently used to collect and display physiological data, and accuracy and immediate decision-making are crucial for effective patient care. The health monitors perform to collect continuous data efficiently by using non-invasive sensors from less seriously ill patients in various clinical environments such as hospital's medical-surgical units, labor, and delivery suites, nursing homes, or patient's own homes to detect unexpected life-threatening conditions or to record routine but required data.

In general, patient monitoring watches warn against serious or life-threatening events in patients with critically ill or abnormal conditions. Patient monitoring systems are defined as "Continuous or repeated observations or measurements of the patient, physiological function, and the function of life support equipment, for supervisory management decisions, including when to make therapeutic interventions, and assessment of those interventions" [98]. A patient monitor may not only alert nursing staff about possible life-threatening events but also provide physiologic input data used to control the connected life-support devices or interfacing units directly.

In the recent past decade, the use of computers has seen significant growth to assist healthcare providers in the collection of data, storage, and decision-making by interpretation of clinical data, along with alarming and alerting by making therapeutic recommendations[99]. In

the recent past, most clinical data were in the form of displaying vital information like Heart and respiratory rates. However, they include integrating data from bedside instruments and other sources outside the intensive-care unit. Nowadays, as systems have become advanced, the use of these systems not only with patients in ICUs but, in some situations, using these systems by patients at home. However, the general principles and usage techniques apply to other hospitalized patients.

Patients who need physiological monitoring are broadly categorized into five types:

1. Patients having irregular physiological regulatory systems, like drug overdose or anesthesia.
2. Patients having a suspected life-threatening condition, like a heart attack or abnormalities.
3. Patients at higher risk of developing a life-threatening condition post-surgery.
4. Patients in a critical physiological state, for example, shock, trauma, or Hemorrhage.
5. Mother and baby during the labor and delivery process.

Healthcare for critically ill patients requires prompt and accurate decisions so that life-protecting and life-saving treatment can be appropriately applied. Because of these requirements, the usage of these monitoring systems has become universal for the purposes mentioned below:

- To collect physiological data frequently or continuously, such as Vital parameters
- To communicate acquired data from data-producing systems to remote central locations.
- To store the continuous data, organize the database, and report data.
- To integrate and correlate information from multimodal data sources.
- To provide advisories and clinical alerts based on data from multiple sources.
- To work as a decision-making tool that health professionals may use in nursing.
- To measure and assess the severity of illness for patient classification purposes.

2.1.2 Monitoring Systems development brief history and challenges

The earliest known detail for acquiring physiological data is during the end of the renaissance period [100]. In 1625, Santorio published his methods for measuring body temperature using a spirit thermometer and the pulse (Heart) rate timing with a pendulum[100]. The first known scientific report on pulse rate measurement in 1707 by Sir John Floyer was "Pulse-Watch" [100]. The first known scientific report published during the period 1852 on a course of fever for a patient was plotted by Ludwig Taube [100]. Later, with successive improvements in the clock

and the thermometer, the record of pulse rate, temperature, and respiratory rate became the standard vital signs for monitoring.

The sphygmomanometer device (blood pressure cuff) was introduced in 1896 by Scipione Riva-Rocci, and arterial blood pressure is measured as the fourth vital sign[101]. Nikolai Korotkoff, a Russian physician, applied Riva-Rocci's cuff with a stethoscope developed by the French physician Rene Laennec to allow the auscultatory measurement of both systolic and diastolic arterial pressure [101]. In the early 1900s, Harvey Cushing, a preeminent US neurosurgeon, predicted the need for and later insisted on monitoring routine arterial blood pressure in the operation theatre [101]. Thus, in 1903, Cushing stated that vital sign measurements should be made routinely with accuracy, and from the 1920s, all four vital signs were recorded during patient nursing[102]. Wilheim Einthoven developed the string galvanometer in 1903 to measure the electrocardiogram [102]. He won the Nobel Prize in physiology for this work in 1924. Thus, ECG has become an essential vital test for acutely and chronically ill patients during treatments. Since then, continuous measurement of vital health parameters has become routine in monitoring all critically ill patients [103][104]. At the same time, advancements in monitoring have been made. One of the significant changes is bringing in computer-based monitoring by integrating various vital functions to monitor bio-signals using non-invasive sensors[102]. Since then, advancements in sensors and their integration of multisensory fusion data [103] in computation using advanced algorithms have made a prompt quantitative evaluation of measured physiological variables[104]. It became essential in decision-making as physicians applied new therapeutic interventions such as ventilators, cardiopulmonary bypass equipment, and electrolyte support.

In recent past few decades, the trends in technology advanced in various areas of monitoring systems design, such as the usage of advanced microcomputers[105][106], semiconductors[107] [108], sensors, equipment & interfacing materials, data processing, storage or display or in communications. Due to these technological advancements, the systems have become complex and may impact [109][110] the following areas in the scope of continuous improvements for safe use. Such as:

- Reduction of insignificant failures
    - Improvements in safe algorithms to trigger alarms for healthcare givers.
    - Effective fault detection algorithms

- Reduction of Hardware failures
    - Data acquisition mechanisms
- Reduction of Software Failures
    - Improvements in signal and data processing algorithms
    - Improvements in decision making mechanisms for nursing staff
- Availability and continuity of the System operation in need.
    - Improvements Fault-tolerant algorithms for safe usage

2.2 Investigation of Heath Monitoring Instrumentation Failures

2.2.1 Motivation to Study Failures in Medical Systems

Computational Intelligence & Analytics Software with advanced electronics is expanding in engineering modern medical systems[111]. These smart technological advancements in systems increase complexity, and their usage in health care raises the question of how medical professionals, patients, developers, and regulators can be confident in the device's safety, reliability, and security[112]. Review [113] of the recent past decade of product recalls[114][115][116], reported [117][118] as of 2018, to the regulator, Food and Drug Administration (FDA) US, shows a significant rise of 126% increase in product recalls, where the majority of the common causes due to software (SW) faults and design-related faults[119][120][121][122].

The software-related errors/faults [123][124][125][126][127] in medical equipment have caused people's deaths in the past, so the issue is not merely theoretical but requires a more in-depth systemic analysis to mitigate the issues by identifying the root causes.

Moreover, it motivates engineering the systems to be designed in more resilient systems [128] by focusing on safety to resolve failures by effectively performing the fault classification and detecting the actual faults [58].

As shown in Figure 1, these faults are in two main categories derived from the common causes, such as

1. Systematic failures like safety instrumented function(SIF) design errors, Hardware(HW) design errors, HW implementation errors, software errors, Modification/Updating Errors, Installation Errors, and

2. Random hardware failures like Stress and Ageing.

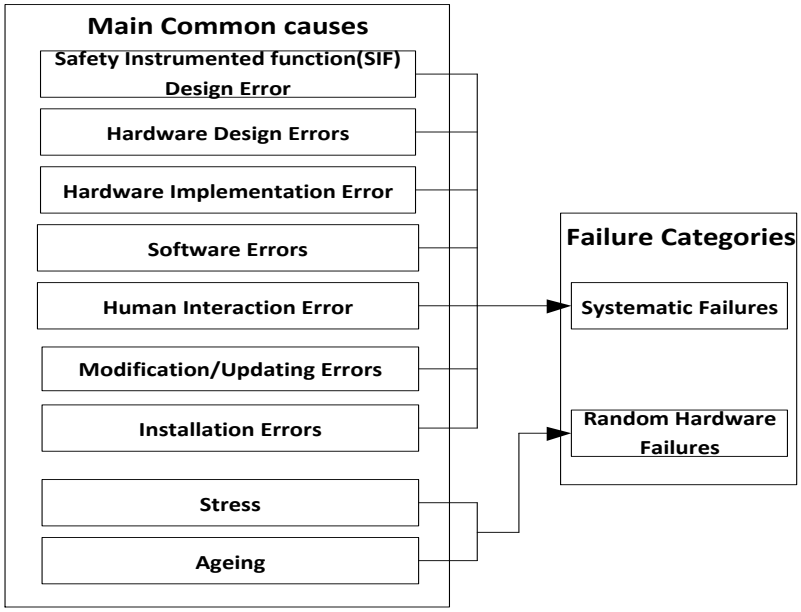


Figure 1: Fault Classification of Common Causes and Failures.

2.3 Investigation of Electronic Medical Systems and its failures

Recent studies [118][129][130] indicated that most vital patient monitoring medical systems follow IEC 60601, related specific standards [131][132], and various design implementation techniques [133][134][135] for better safety. Moreover, it has been further reported [136][137][138][139] that there is a possibility to measure the same vital parameter by monitoring diverse biomedical signals using various sensors. However, all the mentioned studies have common limitations. Most of the related medical systems have been designed in 1oo1 (One-out-of-one), i.e., one sensor measures one or more vital parameters but stops functionality and generates an alarm if any disturbance occurs as a safety [135].

2.3.1 Review and study of similar works in mitigation of common cause failures

Various systems have recently been developed to mitigate the common cause of failures using various safety methods [140 – 167]. A detailed review was performed on these systems, which use safety-related architectures. An assessment of safety and the challenge of mitigating common cause failures can be identified in four industries: aircraft, chemical processing, rail transportation, and nuclear power plants(NPP). As demonstrated by concrete cases, the proper application of various safety-related architectures and diversity are described in [135][225] with guidance shown in Table 1,

Table 1: Comparison of safety usage in system areas to mitigate CCFs.

System Areas	Aviation	Railway	Chemical	NPP
Equipment	X		X	X
Design			X	X
Function	X	X	X	X
Human	X	X	X	X
Signal		X	X	X
Software	X	X	X	X

Over the past few decades, researchers have also looked into different proposed solutions for system failures. For example, I.Tumer et al. [140] came up with a Functional Failure Identification and Propagation (FFIP) framework, which is a graphical evaluation tool that includes a functional system model, a configuration model, a behavior model, a system behavior simulator, and a function failure logic reasoner[141]. FFIP is based on combining hierarchical system models with behavioral simulation and qualitative reasoning. S.Hussain et al. [142] used the Fully Connected Cascade(FCC) Neural Network(NN) and proposed the Sensor Failure Detection, Identification, and Accommodation (SFDIA) Scheme. CL Lee et al. [143] proposed an improvement in the trip setpoint determination methodology that incorporates a design basis event and a beyond design basis event. Y.Li et al. [144] proposed a complementary dual-modular redundancy (CDMR) scheme to mitigate the effects of soft errors. However, it is a two-stage voting system implemented in CDMR. Y.Kimura et al. [145] provided a microprocessor-based system for processing redundant instrumentation signals with a complex trip function, including self-testing and fail-safe feature [146] in place of a conventional hardwired 2oo3 trip circuit. Abdali et al. [147] proposed a fault-tolerant three-tier architecture that supports data flow from body sensors to the cloud. The systems are wearable computers, mobile computing, and mobile cloud computing, which feature high possible fault tolerance due to the nature of their components. Various self-checking voting mechanisms in dual and TMR architecture schemes[148][149][150][151][152] were investigated to improve the functional safety of hardware and software. A detailed review is performed on methods [153] such as traditional methods like Failure Mode Effective Analysis (FMEA) [154][155], System(S)FMEA, Design(D)FMEA [156], Fault Failure Analysis [157], Decision Tree Analysis, Preliminary/System Hazard Analysis(PHA/SHA) and few fault-tolerant redundancy techniques [158][159]like Hot/Warm stand-by [160][161][162][163][164] and Cold stand-by

[165][166][167] usage. However, we noticed that there are limitations to environmental conditions, usage, and level of reaction to the failure [135].

In this present digital age, with advancements in technology, medical systems are evolving from analog to digital and simple to complex systems. Over the last decade, due to rapid growth in technology and innovations, the systems are shrinking in size. Therefore, much demand arises for new methods to mitigate the challenges to make the medical systems resilient & reliable along with safety improvements. In critical pre- & post-monitoring of the patients in ICU scenarios, if any abnormal condition occurs, a system should provide timely notification to operators, and performance should degrade gracefully rather than abruptly, especially in life-sustaining medical systems. This level of capabilities for a reliable safety system requires mainly Availability & Reliability [168] of measurements in any given scenario [169][170][171]. It also needs reliable sensing with or without redundancy structures[172], system modes of operation[173] and real-time response, self-monitoring built-in test functions[174], well-organized fault identification and isolation of faults with safe degraded function, a well-defined system negation mechanism for all types of errors, to generate the related alarms. Overall, the system should meet the guidelines set by standard IEC 61508 and IEC 60601(Medical devices) for the best practice of functional safety [175][176]. On Safety, the standard IEC 61508 specifies about functional safety of electrical/electronic/programmable electronic safety-related systems. It has defined four different safety integrity levels as a common measure with low and high modes for measuring risk reduction Table 2. An embedded electronic medical system is also a safety related electronic system, so the standard IEC 61508 can apply to these medical systems. An embedded electronic system can meet the requirements of safety-related systems by definition and follow the developing process to achieve the desired Safety Integrity Level. Thus, having this type of system requirements[177] will reduce false, faulty, or insignificant alarms and enhance the safety feature of the device for consistent vital sign measurements[178].

Table 2: Safety Integrity Levels.

SIL Level	**Probability of Failure on Demand $(PFD)_{avg}$ (Low Demand)**	**Probability of Failure per Hour (PFH) (High Demand)**
SIL.1	$\geq 10^{-2}$ to $< 10^{-1}$	$\geq 10^{-6}$ to $< 10^{-5}$
SIL.2	$\geq 10^{-3}$ to $< 10^{-2}$	$\geq 10^{-7}$ to $< 10^{-6}$
SIL.3	$\geq 10^{-4}$ to $< 10^{-3}$	$\geq 10^{-8}$ to $< 10^{-7}$
SIL.4	$\geq 10^{-5}$ to $< 10^{-4}$	$\geq 10^{-9}$ to $< 10^{-8}$

Furthermore, a detailed study and investigations are performed on various embedded platforms that use microprocessors(CPUs) or microcontrollers(MPUs). These advanced computing devices (CPUs/MPUs) range from 8-bit to 64-bit data processing capacity, which makes Single Board Computers (SBCs), System on Chip(SoC), and System-on-Modules(SoM) incorporating single or multiple processor cores used for various applications. These embedded hardware computing platforms, essential instrumentation, and appropriate software technology are suitable for medical systems and compatible with a wide range of medical applications [241][242].

In addition to the previously mentioned medical systems in section 1.1, which measure and monitor vital parameters, various medical systems are also designed using embedded hardware and software technology. Table 3 presents a critical system that measures vitals and crucial organ functionality health [241][243][244].

Table 3: Various embedded system applications in the medical field

Key Categories in Medical Systems	Few Medical Systems And its Application Examples	Embedded Systems/platforms for research
Invasive Systems	Pacemakers, Defibrillators, Infusers for Drug Management	Beagle board, Raspberry PI, along with instrumentation system.
Non-Invasive Systems	Mobile Patient Monitoring Systems, Surgical Robots, Therapeutic Nanomachines, Ventilators Medical Imaging Systems, Biotechnological Analyzers, Xray Systems	High-end computing platforms with single/dual/quad cores of ARM cortex family with in-build GPU & co-processors for multitasking from TI-Sitara, NXP iMX.6D/6Q/8D/8Q families or Intel ES platforms like ATOM ES, for parallel processing with FPGAs, using CCD camera sensor systems, digital radiation scanners, and various instrumentation as per specifications.
General Medical Systems	Nurse Call Systems, Patient Queue Systems, Radiology Prompting Systems, Drug Expert Systems, Drug Administration, Therapy Management, Electronic Health Record, Electronic Patient Record.	Intel Atom ES, Beagle board, Raspberry PI, along with instrumentation system, GPS, GSM, Node MCU, Arduino, mobile phones..etc.
Point-of-Care devices	Portable Diagnostic Systems, Body Scanners, Blood Gas Analyzers, Pulse Oximeters, Glucose analyzers	Arduino, Microchip PIC MCU, Atmel MCU, Beagle board, Raspberry PI, along with instrumentation system.

The study shows that most embedded platforms are used for medical systems in 1oo1 high safety architecture, with all safety mechanisms incorporated into the systems in compliance with the IEC standards. However, implementation of fault-tolerant is cost-intensive and cumbersome to make compliance.

This study proposed an FPGA-based fault-tolerant safety-related design approach that uses strategies like 1oo2- (one-out-of-two), 2oo2- (two-out-of-two), 2oo3- (two-out-of-three), or MooN (M-out-of-N) logic for reliable sensing and computation of vital cardiac parameters like heart rate [26][179]. The design combines electrocardiogram, phonocardiogram, and photoplethysmogram sensors into a hybrid sensor for reliable sensing. These sensors are connected to each channel independently. A safe voting function uses Pearson's correlation coefficient method to compute the correlation coefficient 'r' between the heart-rate values measured from independent, diverse channels. The resultant coefficient 'r' is used by a fault-tolerant de-gradable safe function & built-in test function for isolation of fault and enables a reliable heart-rate value for display at no-fault conditions. This safe function uses negation error codes to generate the related alarm for each significant detected fault and log the results. With Bland–Altman and correlative plots, the accuracy of heart rate measurements and the correlation between vital sign measurements from two channels are analyzed. The recorded failure detected signal & heart rate measurements at each channel output, along with results of safe function output, are analyzed for effective functioning of fault isolation and reduction of a single point of failure (SPOF).

The current doctoral research project focuses primarily on reducing SPOF and fault alarms by using Safety-related architectures without redundancy and a fault-tolerant safe degraded algorithmic function for continuous and consistent vital sign measurements. This design approach contributes to the system's high availability with consistency in vital sign measurements. Availability of the system explains that both channels should detect a failure for the system to fail, or at least one channel functioning is enough to operate the system. It further explains how diverse sensors measure the same single cardiac vital sign parameter in parallel channels. The results are correlated with a safe voting function for consistent vital sign measurements. Thus, evaluating these results by additionally applying the pathological data helps obtain a state-of-the-art medical device for further research studies on monitoring various organs for early detection of various abnormalities.

2.3.2 Areas of Safety Improvements in Medical Systems and their Necessity

A detailed study performed on a broad spectrum of existing medical systems, from wearable diagnostic systems to complex surgical medical systems, identified a few areas for safety

improvements in line with the research challenges mentioned in the published reports [113][129][135][180].

As shown in Figure 2, we focused our primary research on critical areas. We proposed a fault-tolerant safety-related design architecture for medical systems. We validated these configurable architectures [181] to achieve the desired objective, like the uninterruptible operation of the systems with reduced false alarms and reliable vital data, which is needed for good nursing. Thus providing this safety platform and utilized to explore the applicability of data analytics on the bio-medical signal data to get accurate vital data and predict the subject's health abnormalities. Similarly, data analytics on the end-of-life parameters of multimodal system electronics, sensors, and components provide system safety improvements by PdM instead of planned preventive maintenance(PPM)[182].

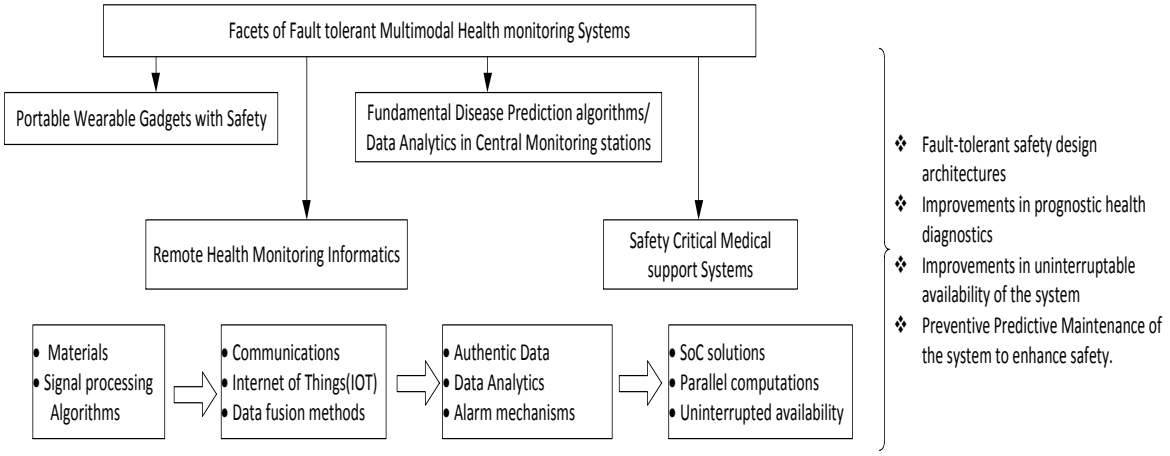


Figure 2: Areas of Safety improvements in Medical Systems.

Furthermore, in our continuous study and investigations on similar works such as on the reduction of false alarms, improvement in operational up-time in the existing medical monitoring systems reveals that more than 80% to 90% are false alarms and estimated that only 85% to 93.5% operational up-time [113][245][247][248][250]. In the recent past, a comparison study of new and old models of pulse oximetry during motion-resistant evaluations revealed that 71% to 95% of alarms are false[246]. There are attempts made in various areas of medical systems, including clinical alarm management systems in ICU, using smart algorithms and techniques to reduce false alarms [247][249][251][252][253][256]. A POC device such as pulse oximeter built on the Arduino platform achieved a sensitivity of 99.29%, specificity of 95.31%, and accuracy of 97.76% by using algorithms and features like hierarchical decision rules by combining with

simple features such as absolute amplitude and threshold crossing rate, and autocorrelation function and seen a reduction of false alarms by 95.31% [250]. Below, Table 4 presents the comparative study of existing commercial medical devices and the methods and techniques used for improving the identified parameters, such as "reduction of false alarms" and "increase of Operational time."

Table 4: Comparative study of existing medical devices safety improvement parameters

Medical Devices Name	Existing Commercial Devices [113][245-254]			
	Commercial Device Names	False Alarms % approx.	Uptime /availability % approx.	Improvement methods/techniques used for ("reduction of Alarms")
Patient Monitors Systems	Phillips Spacelabs-Medical GE	Over all ~90%	80% to 93.5%	--Average of defined parameter(~40%) -- Delay of ~19 Sec and patient care & medication(~65%) -- Threshold adjustments (~95%) -- Multi-signal processing (~85%) -- Smart algorithms(~90%) -- Majority voting(72.5%). -- Neutral networks (92.5%) -- Bayesian technique(84.3%) -- Fuzzy logic (80.6%)
Pulse Oximeters	Nellcor Criticare Masimo	71% to 95%	~98%	

2.3.3 Research Problem Setting

Biomedical Signals monitoring and diagnosis must be carefully checked so people do not get the incorrect medication. In addition, the parameters measured by the HHMS, specifically CHMS, measure heart rate (HR), blood pressure (BP), and other related vital parameters, need to be effectively diagnosed for illness and disease symptoms to do proper nursing.

The patient's pre and post-operation health monitoring and diagnosis are particularly important for effective nursing. These diagnostic systems should present authentic health monitoring vital, non-vital uninterruptedly, and desired parameters, even if any disturbances occur during critical monitoring periods for a patient. In real-time, the systems should uninterruptedly present authentic vital health monitoring measurements. It involves specific challenges like systemic failures and random failures. These critical systems are known to replenish continuously, but the mechanisms involved are inadequate and largely unknown to mitigate these failures.

Our main research problem addresses these challenges and improves fault identification and analysis mechanisms. The system should uninterruptedly present authentic vital health

monitoring measurements and improve the accurate predictability of the illness with pathological completeness. Thus, the vital sign measure is so important that it improves the predictability of various heart-related diseases(HD) or cardiovascular diseases(CVDs), such as Arrhythmia, Heart failure, Valve disease, coronary heart disease, peripheral heart disease, Aortic disease, congenital heart disease, deep vein thrombosis(DVT), etc. For this, we preferred to investigate these human health monitoring systems by using safety-related design architectures and the generation of the next technologies to counteract such failures. So, they are used in designing and developing fault-tolerant systems with or without redundancy, running-time monitoring, and implementing fault diagnostic algorithms.

The present available medical systems, specifically non-invasive HHMS and related POC medical systems used for diagnosis, may not be embedded with approaches like redundancy and fault-tolerant mechanisms, which may be due to cost and technological factors[183]. However, applying these approaches to this system improves authentic health monitoring and symptom diagnosis if the failures are mitigated. Further, applying correlation techniques to diagnostic data of the patient and system health data will provide relevant new insights towards pathological completeness in the identification of the patient's illness and the health of the electronic system.

Thus, implementing a fault-tolerant safety-related design approach and studying the correlation of data inline to system health parameters will significantly improve our understanding of the fault-tolerant diagnosis of the patient's illness. Furthermore, using AI-based predictive maintenance (PdM) techniques in these monitoring systems further helps in the resiliency of the systems. It may open up a new avenue in sensor fusion technology advancements with AI.

2.4 Research Objectives

This doctoral research project evaluates the safety-related design architectures usage in specific CHMS or a general safety-critical patient monitoring system and low-cost POC medical devices.

The research project's main objective is to investigate the implementation of safety-related design architectures like 2oo3 (two-out-of-three), 2oo2 (two-out-of-two), 1oo2 (One-out-of-two), and its related safe computational approaches based on the selection of monitoring vital parameters of human being. Furthermore, these collected data evaluations and their computational approaches apply to new areas in further advancing medical systems by using-in

methods & technologies like smart fusion sensors, machine learning, data analytics, artificial intelligence, and the internet of things (IoT)[184].

By sensing the subject, we intend to collect data from multimodal sensor fusion elements in a non-invasive mode. Furthermore, the biomedical signals collected from a specific organ like the Heart have been analyzed and diagnostic correlative computations have been performed in line with these safety-related approaches. Thus, these research studies help in the improvement of mechanisms by addressing the challenges and achieving the following objectives:

- To evaluate the improvement in providing uninterrupted authentic vital data in the usage of a safety-related design approach in the design of HHMS.
- To assess the improvement in reduction of undesirable spurious alarms for any single point failures in the usage of fault-tolerable safety-related architectures.
- To evaluate the system's components remaining useful life (RUL) period by performing predictive data analytics on the system component's usage life. This assessment provides PdM support to the system, which drastically improves the system's safety.

The availability of diagnostic systems with functions like fault-tolerant, multimodal sensor fusion interfaces with portable or wearable devices is limited in present systems.

In this thesis, we proposed to design and develop a portable and wearable medical monitoring system prototype using safety-related architecture. This system collects the data from three different sensors, such as ECG, PPG, and PCG, by detecting electric potential, light, and sound signals via non-invasive.

As a strategy, we design three independent and diverse computing channels using ECG, PPG, and PCG sensors. A validated algorithm is used in each channel to measure the heart rate. In addition, correlative diagnostic algorithms and related procedures are developed to evaluate the implemented safety-related architectures.

To predict the illness effectively, we decoded the multimodal data acquired by processing the various biomedical signals, and data analytics that were performed with correlative algorithms to unravel the illness. In addition, a smart wearable sensor-fusion suite was designed to efficiently capture data for investigating identified illness parameters, such as cardiac disorders.

The ultimate objective is to provide a mechanism for human health monitoring systems using safety-related architectures to effectively improve prognosticating illness. These safety-

related multimodal fault-tolerant studies need to combine with the pathological studies and help develop various gadgets, from point-of-care devices to safety-critical patient monitoring systems, with the aptness of usage in the monitoring of various organ's health. Additionally, this research-platform supports further research in developing AI-based sensor fusion systems. These medical devices embedded with histopathological studies further help predict the illness more effectively.

2.5 Scope of the present work

This thesis aims to research the possibilities of providing aptness usage of Safety-related architectures in the design of Non-invasive human health monitoring systems and point-of-care Medical systems with fault-tolerable and portable multimodal sensors. It is done by mitigating the teething challenges, achieving the outline objectives mentioned in section-2.4, and providing a platform for further research scalability to improve predicting diseases at early stages.

Used Correlation techniques like Karl Pearson’s coefficient of correlation method in realizing safe functions like fault detection and identification logic, correlation coefficient-based safety function, and fault-tolerant safe degradation switching mechanism for authentic vital measurements of a human being. These functions are used in safety-related design architectures like 2oo2 and 2oo3 for segregating the authentic vital data for prognostics. These outcomes are compared against 1oo1 architecture for improvements in the reduction of alarms and system availability and measured positive predictive values (PPV) and sensitivity (Se) on authentic data.

Altogether, 200 patients were available for vital HR parameter measurements and system-level evaluation in 2oo2 and 2oo3 configurations following application protocol. Using MATLAB software tool, developed GUI-based application software for configuring the CHMS system and capturing the measured sample data for further analytics.

Chapter 3 details the safety-related architectures 1oo1-, 1oo2-, 2oo2- and 2oo3- and describes their apt usage in developing the CHMS instrument prototype with three independent channels based on ECG, PPG and PCG. Explained the correlation method used in safe logic development, experimental set-up, and evaluation framework. An application protocol has been described and followed to capture the sample data and evaluated using a GUI-based CHMS configuration tool developed based on MATLAB software. Finally, an experimental case study has been presented by configuring the CHMS system in 2oo2 using two independent channels of

ECG & PCG and showcased the results with improvements in the reduction of spurious alarms significantly.

Chapter 4 focuses on developing and optimizing a fault-tolerant human health monitoring system based on 2oo2 architecture using ECG and PPG channels to separate authentic data from system-level failures effectively. Further, it presented an evaluation framework and safety functions to accurately segregate normal and abnormal data on vital human health measurements for further prognostics. Functions such as AND-OR safety function, correlation-based safe function, and fuzzy entropy-based detection technique are used for the vital measured in terms of positive predictive values (PPV) and sensitivity (Se) on authentic data.

Chapter 5 focused on improvement parameters like systems availability and developed an authentic measure of vital sign HR using a fault-tolerant design approach with safety analysis using 2oo2 architecture using independent channels ECG and PPG. Using the correlation technique, presented the safe degradation function, fault detection and fault-tolerant logic. Evaluated the 5-concepts in various diverse modes and presented a cause and effect analysis.

Chapter 6 detailed the enhancements of safety analytics using an edge-AI-enabled triple module redundancy design approach using three independent channels, ECG, PPG, and PCG, to improve systems availability parameters.

2.6 Contributions of this Thesis

Until recently, most human health monitoring systems used 1oo1 design architecture due to its high safety. However, design compromises may enable it to creep into spurious failures, causing frequent alarms and reducing the system operability time.

Here, we attempted to use the apt use of Safety-related architectures in the design of Non-invasive HHMS and POCT systems with fault-tolerability. The main contributions of this part of the research are:

- Architecture for segregation of human health parameters from system health parameters and finding authentic data for prognostic analysis.
- Effective segregation of human health data into normal and abnormal patient data for prognostic analysis.
- Improvement in system operability through 2oo2 and 2oo3 safety-related architectures.

2.7 Preparing for Tomorrow, Today

Microcomputers and related developments have substantially improved the capacity of medical systems to produce and analyze physiological data needed in patient monitoring systems. However, there is still a need for improvement in using microcomputer-based portable devices in healthcare facilities or patients' homes. Many challenges, including false alarms, insignificant failures, etc., remain in the research of how microcomputer-based systems could mitigate the issues by successfully integrating, assessing, and simplifying the complex data needed in care for critically ill patients.

Chapter 3. Introduction to Fault-tolerant Architectures for Medical Designers

3.1 Essentials of Biomedical Instrumentation System

Biomedical engineering is the interaction of engineering and medical disciplines. This area of expertise supports the resolution of issues within living systems via the use of relevant knowledge and technology. This instrumentation system, for example, is used to diagnose, treat, and prevent human disease. Biological signals generated by the human body, such as electrical, optical, or acoustic signals, are also monitored by several in vitro medical systems. Concepts of electronics, safety mechanisms, and measurement techniques are needed to measure these biological signals and design a medical instrument. As the medical field is evolving, the area of biomedical engineering is expanding at a rapid pace.

Technology advancements bring in the sophistication of electronic medical instruments, and presently the usage of computers is becoming increasingly crucial in biomedical systems/devices. These microprocessor-based medical instruments are to do various small or large tasks in a single or multi-purpose instrument with multimodal interfaces to the extensive computing power needed to process a large amount of information in a medical system. However, commonly, these devices have certain essential components and consider following certain vital factors when designing a medical measuring instrument.

In general, any electronic medical instrument consists of the following functional essential parts:

- **Measurand:** A physical quantity, and the instrumentation systems measure it. The human body is the source for this measurement, generating bio-signals. Example: body surface or blood pressure in the Heart.
- **Sensor / Transducer:** The transducer converts one form of energy to another, usually electrical energy — for example, the piezoelectric signal, which converts mechanical vibrations into an electrical signal. The transducer produces a usable output depending on the measurement. The sensor senses the signal from the source and interfaces with the human.
- **Signal Conditioning Circuit:** Signal conditioning circuits convert the transducer's output into an electrical analogue value. The instrument system sends this quantity to the display

or recording system. Generally, the signal conditioning process includes amplification, filtering, analog-to Digital, and Digital analog conversions. Apart from this, signal conditioning circuits compensate for the non-idealities of sensors. Signal conditioning improves the sensitivity of instruments.

- **Display:** It visually represents the measured parameter or quantity—for example, a Chart recorder, Cathode Ray Oscilloscope (CRO). Sometimes, alarms are used to hear the audio signals. Example: Signals generated in Doppler Ultrasound Scanner used for Fetal Monitoring.
- **Data Storage and Transmission:** Data storage is used to store data and can be used for future reference. In recent days, Electronic Health records have been utilized in hospitals. Data transmission is used in Telemetric systems, where data can be transmitted remotely from one location to another.

Nowadays, in every electronic medical device/system, the essential components are built upon microprocessors, power supplies, enclosures, cables, indicators, displays, and alarms. Therefore, some of the critical factors that need to be considered when designing a medical measuring instrument include:

- **Patient safety considerations:** Medical instruments must be physically connected to the patient. There is the possibility of an electric shock hazard in cases where there is electric or electronic equipment unless adequate measures have been taken to design the medical equipment to prevent such hazards. Therefore, all safety measures must be ensured during the operation of the medical instrument.
- **Transducer interface problems:** All instrumentation systems are affected in some way by the presence of the measuring transducer. This problem may get compounded while measuring the living system, where the physical presence of the transducer may change the reading significantly. Besides, the presence of a transducer in one system can affect the response in other systems. Therefore, adequate care must be taken while designing a medical measuring system to ensure that the loading effect of the transducer is minimal on the source of the measured variable.
- **Measurement range:** Generally, physiological signal measurement ranges are quite low compared to other parameters outside the medical field. The biomedical signals are

usually very small in the microvolt range. Therefore, it is important to consider this when designing any medical instrument.

- **Frequency range:** Most physiological signals are in the audio-frequency range or below. Also, many signals contain dc and very low-frequency components.
- **The high possibility of artifacts**: An artifact is an undesirable signal extraneous to the physiological variable under measurement. It may come from electrical interference, cross-talk, or noise generated within the measurement system. Designers of biomedical instruments put in ways to remove/filter or avoid these artifacts.
- **Reliability:** In life-saving instruments like defibrillators, failure to operate or provide the desired output can cause a potential life threat to the patient. Hence, biomedical equipment must be reliable, easy to operate and withstand physical stress like transportation within the hospital or in the ambulance and exposure to corrosive chemicals.
- **Safe levels of applied energy:** Biomedical instruments require some form of energy to be applied to the living tissue, e.g., a CT scan requires X-rays (a form of electromagnetic wave energy). Scientific researchers have established safe levels of some of these energies; designers can use this information when designing medical equipment.

Incorporating the above vital factors in the instrumenting system and product requirements like portability, compatibility, modularity, and scalability of the device for certain functions provides certain challenges to biomedical engineers to design and develop resilient systems.

3.2 Basic Safety in Biomedical Electronic Instrumentation System

The medical system's safety [185] and effectiveness play a vital role in healthcare. Recent technology advancements in electronic instrumentation use various measuring instruments to monitor and control a process. In this area of biomedical electronic instrumentation, improvements in system resilience always help us measure, record, compute and transmit data to or from the body for better nursing. Medical systems are essential to patient care, but if a defective or unsafe device enters general use, it can have severe consequences.

Designing Safety-critical systems is a complex thing involving several fields. In designing a Medical Instrumentation system for safety, the designer plays a vital role in defining

the needed functional requirements and the required safety level based on the involved complexity and the assessed risk[186][187]. The following are the important safety things a designer needs to consider[109]. However, some standards guide medical-device safety, such as IEC 60601-1 – Medical electrical equipment – Part 1: General requirements for basic safety and essential performance[188][189].

- Device Discovery and Concept
- Medical Device Regulations
- Design Controls
- Medical Device Testing
- Risk Management
- Quality Assurance

3.3 Fault-Tolerant Safety-related Architectures

The standards IEC 61508 and IEC 60601(Medical devices) have been referred for the best practice of functional safety and are now recognized worldwide. In the IEC 61508 standard, several architectures such as 1oo2-, 2oo2-, 1oo3-, and 2oo3- are introduced for safety-related systems. However, the selection of the architecture depends on application requirements such as safety, reliability, and availability levels. Here, some of the common architectures are investigated, and evaluate the proposed architectures for suitable for medical monitoring systems to address the mentioned challenges.

1oo1(1-out-of-1): The system is based on a single-channel architecture, shown in Figure 3 and Figure 4, and is typically designed for low-level safety applications. Most point-of-care health monitoring devices and low-cost patient monitoring systems are based on this principle. In this system, if any single failure occurs in the sensor or a device, the output represents a single switch showing wrong results, loss of the safety function, or a process that will dangerously shut down by raising the alarm.

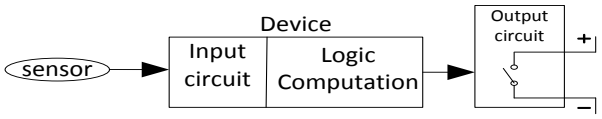


Figure 3: Basic system 1oo1(1-out-of-1) architecture.

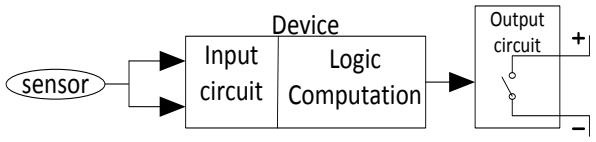


Figure 4: 1oo1-with self-checking pair safety architecture.

1oo2(1-out-of-2): The architecture 1oo2- has two outputs (based on two 1oo1 channels) connected in series, as shown in Figure 5. Thus, the system improves the performance of the safety integrity of the system since any single contact is required to shut down the process by raising the alarm. However, the disadvantage is that it increases twice the potential for nuisance failures. Thus, neither 1oo1- nor 1oo2- architectures can reduce the potential failures or alarms. However, self-diagnosis and switching the mechanism to 1oo1 can be explored.

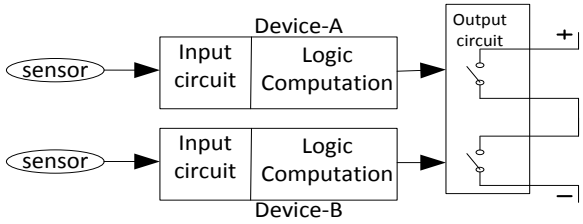


Figure 5: 1oo2 (1-out-of-2) basic safety architecture.

2oo2(2-out-of-2): The 2oo2- has two outputs (based on two 1oo1- channels) connected in parallel, as shown in Figure 6 and Figure 7. The advantage is that if the system goes for a dangerous shutdown, both channels should fail to raise the alarm. Else if any single channel is functionally operational, the system operates normally. Thus, this system can reduce potential failures or alarms by implementing additional safety measures like diverse sensors and diverse algorithms for computations in each channel.

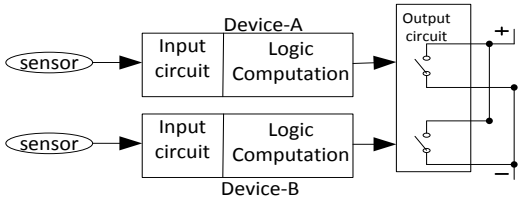


Figure 6: 2oo2 (2-out-of-2) safety basic architecture.

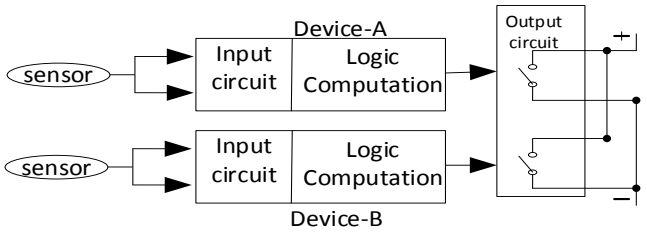


Figure 7: 2oo2(2-out-of-2) with dual self-checking pair safety architecture.

2oo3(2-out-of-3) or Triple Module Redundancy (TMR): The 2oo3-based system has three channels with three outputs connected to a complex output voting circuit, as shown in Figure 8.

The system advantage is that if the system goes for a dangerous shutdown, any two channels should fail to raise the alarm, i.e., The system continuously operates even when any single channel dangerously fails. These 2oo3 systems (TMR) or, similarly, 2oo4- quadruple modular redundancy(QMR) are usually used in fault-tolerant applications, where the system must continue functioning despite a failure—most often in life-support medical devices. Thus, these systems can reduce potential failures or alarms by implementing additional safety measures like diverse sensors and diverse algorithms for computations in each channel.

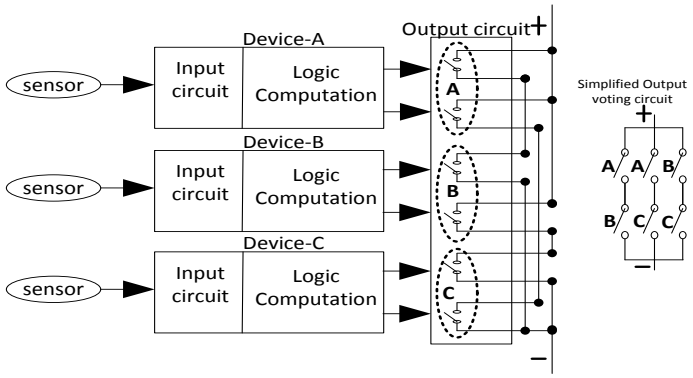


Figure 8: 2oo3 (2-out-of-3) basic safety architecture.

Referring to [135] and based on the above investigations, the 1oo2-, 2oo2-, and 2oo3-architectures are suitable due to safe and high availability with diverse redundancy. The possibility of fault-tolerance and system functional operation continuity can be achieved using a safe system degradation mechanism with proper log data analytics. These architectures can be configured based on medical systems' health parameter monitoring.

3.4 Types of Bio-Medical Signals and their Multimodal Analysis

The signals that are obtained from the human body during the investigation and used as primary sources of information for investigating the body site under test are called biomedical signals. The process of extracting the information from the biomedical signals is as simple as sensing a person's pulse on the wrist or as complex as analyzing the structure of internal soft tissues by an ultrasound scanner. Biomedical signals originate from different types of sources.

3.4.1 Bio-electric signals:

Nerve and muscle cells produce these signals owing to the potential difference induced by ion transfer between cells. The resultant potential difference is measured using the appropriate electrodes. In addition, many cell interactions inside the body generate these signals. ECG and EEG (Electroencephalography) signals are the most common examples of bio-electric signals.

3.4.2 Bio-acoustic signals:

These signals originate from physiological vibrations such as heartbeat inflation and deflation of the thoracic cavity, peristalsis in the intestine, etc. It provides information about underlying biological phenomena. Examples of such signals are the flow of blood in the heart, through the heart valves, and airflow through the upper and lower airways and in the lungs, which generate typical acoustic signals.

3.4.3 Bio-mechanical signals:

These signals originate from some mechanical functions of the biological system. These include motion and displacement signals, pressure, and flow signals.

3.4.4 Bio-optic signals:

These signals are generated because of optical functions of the body, occurring either naturally or induced by the measurement process. A typical example is the pulse oximetry signal obtained from infrared optodes. Here, the measurement process involves measuring transmitted or backscattered light from tissue at different wavelengths.

3.5 Safety-related fault-tolerant design conceptualization

The proposed safe computation and fault detection approach is based on a composite fail-safety principle with 1oo2-, 2oo2-, or 2oo3 architecture. The design architecture comprises three micro processing devices (Device A, Device B, and Device C). Critical safety functions are partitioned and performed by three devices (A, B, and C) with diversity. A fourth device (O) is responsible for safety-related functions. Due to the modularity of this system design approach, the system's architecture is configurable based on the feasibility and importance of the desired parameter to be monitored. Thus, an advantage of concurrent multi-signal, multi-parameter, independent processing, and possibilities of effective correlative analysis of the values can be explored by using this system. Based on the system configuration, such as 2oo3, the three devices (A, B & C) cross-check using interconnection links. Along with the fourth device (O), they perform built-in tests and negation operations as per the defined safe state for each fault detection.

In this system design, functional faults have been attempted to be detected. At each fault detection, a defined safe state generates an alarm, and a negation operation is performed, i.e., a code or a known defined value needs to be generated and recorded for the defined fault/error. This fault/negation value indicates the type of fault/failure.

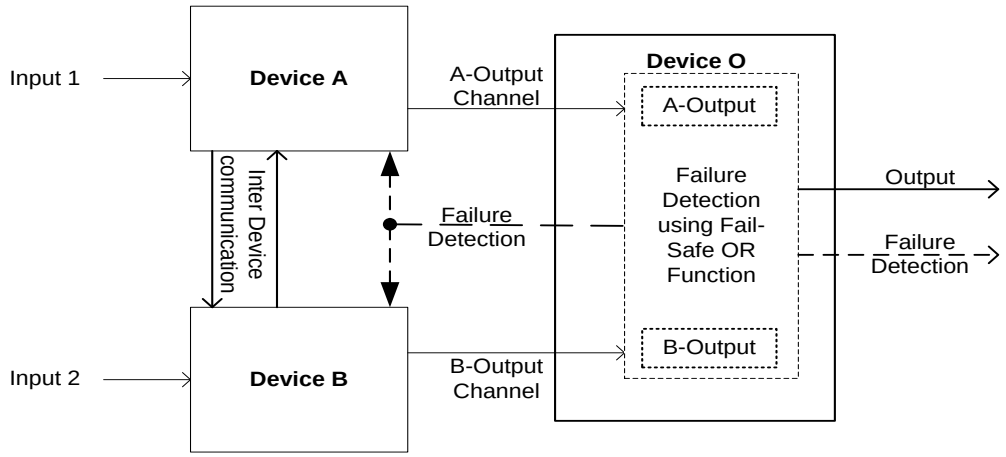


Figure 9: 2oo2(2-out-of-2) Architecture design for HHMS.

The system uses independent device units A, B, C and O with stand-alone diverse computations, and the implemented logic is programmed into each FPGA device, respectively. Thus, the composite fail-safety principle requires an agreement between the three devices, A, B, and C. The feedback loop of failure detection and appropriate execution of negation operation

ensures the fail-safe operations of the system to the incidence of data errors and their effectiveness in reducing the false alarms and ensures the system toward resiliency.

The proposed conceptual design architectures 2oo2- and 2oo3- are shown in Figure 9 and Figure 10.

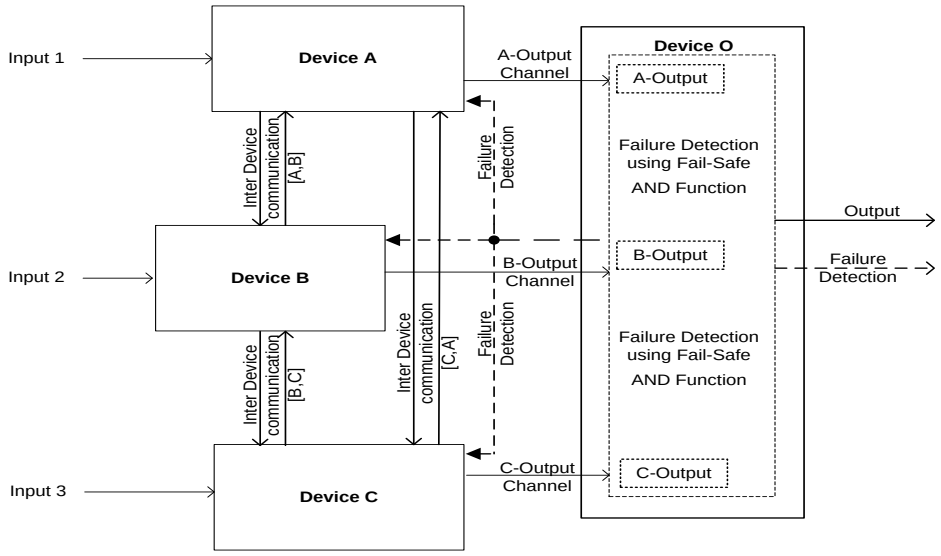


Figure 10: 2oo3(2-out-of-3) Architecture design for HHMS.

3.5.1 Experimental Set-up and Evaluation Framework

3.5.1.1 Experimental Set-up

The experiment was carried out in steps.

- Configuration of the CHMS using GUI
- Preparation of the subject for Experiment
- Sensors placement on a wearable-suite
- Simulation Experiment and Evaluation
- Clinical Experiment

A MATLAB tool-based GUI is developed for configuring the CHMS, as shown in Figure 11. The tool provides: 1. CHMS control panel – which provides options for real-time algorithm model development and evaluation, setting simulation mode and options for analysis; 2. Basic patient information, 3. Device configuration panel, 4. Sensor selection for correlation, 5.

Parameter selection, 6. Safety architecture selection, 7. Diagnosis artifact selection, 8. Signal capture controls, 9. Raw signal to Processed signal capture, 10. Duration record, 11. Report generation.

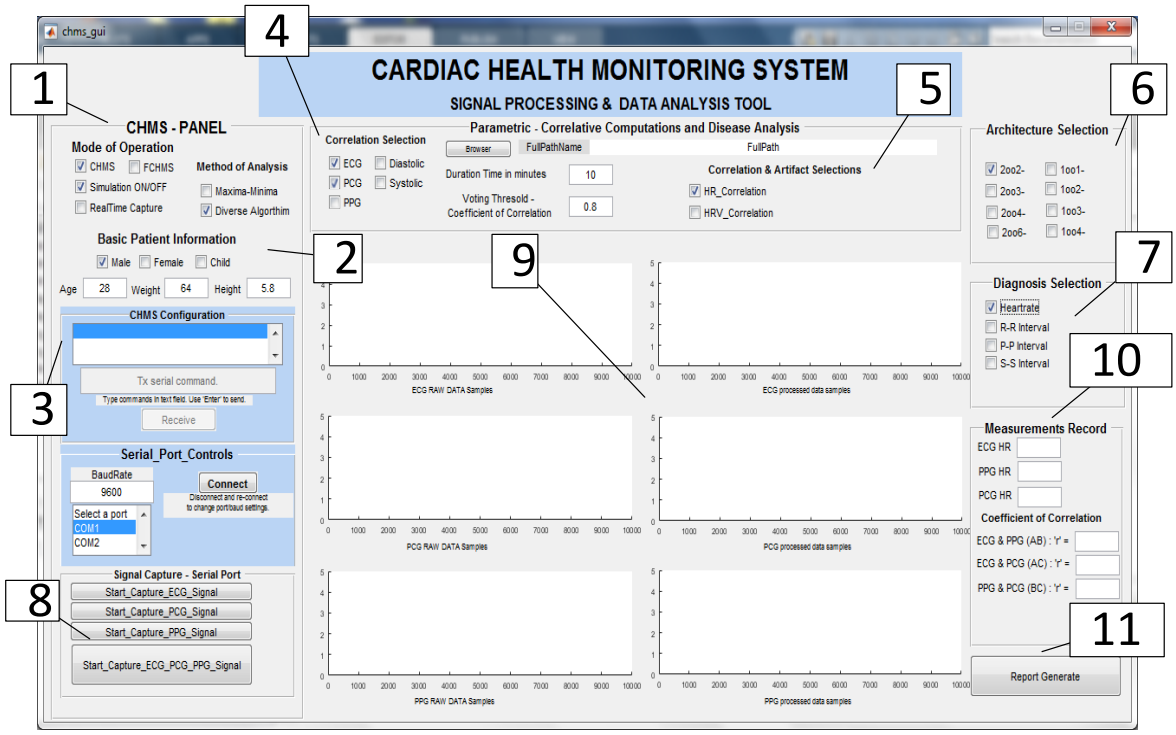


Figure 11: MATLAB-based GUI tool for system configuration and Data sample collection.

Multimodal sensors are placed on a wearable suite and worn by the subject, as shown in Figure 12, connected to the portable monitoring device prototype.

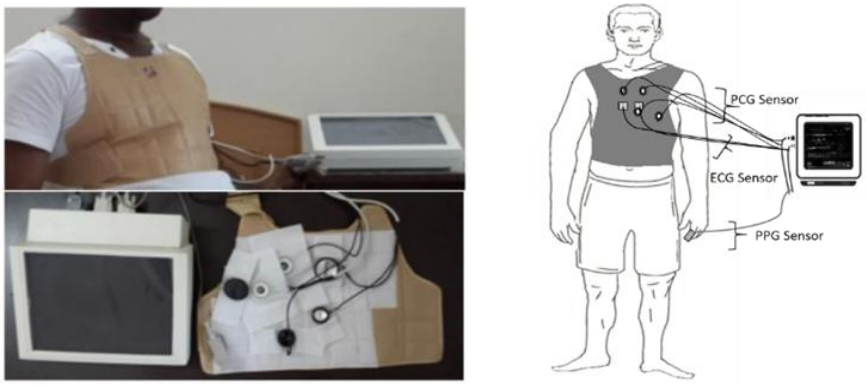


Figure 12: (a) Experimental set-up and (b) CHMS - PPG, PCG & ECG Sensors placement.

3.5.1.2 Application protocol

The system has been validated using data collected from 5 subjects of different age groups following the Declaration of Helsinki. The subjects, aged 15 to 55 years, were available for measurement and testing after obtaining informed consent, of which fifty+ used data from normal healthy patients.

Recommendations before taking measurements:

The advice is much like blood pressure measurement (BP). Most physical or psychological factors can influence the assessment of heart rate. We have mainly adhered to the following:

1. Heart rate can be affected by exercise, alcohol, nicotine, and coffee. These should be avoided for 24 hours before the measurement.

2. The subjects should preferably sit on a chair, not cross their legs, have a comfortable room temperature, and be noiseless before the measurement.

3. The subject should not speak during the measurement, and at least 5 minutes should elapse before the first measurement.

4. Hemodynamic variables must be determined before the heart rate is measured in patients being evaluated for hypertension or heart disease.

5. Avoid measurement in patients receiving pharmacologic therapy. The physician should know that many cardiovascular medications can decrease or increase heart rate.

The CHMS is configured via GUI by activating the ECG and PCG sensors in 2oo2 mode, and the measured heart rate values are recorded over 1 hour for each subject. The recordings were analyzed qualitatively in real-time by the CHMS GUI tool. According to [222], the calculated trigger levels for HRmax (MaxHR), HRmin (MinHR), Targeted HR (THR)-Upper limit & Lower limit levels and Adjustable (ADJ), Upper limit (UL) & lower limits (LL) is set to 5% & 10% for the defined criticality to generate the alarms. The safe logic implementation performs data correlation, generates an alarm for the deviation at '$r_{AB} < 0.5$', and independently evaluates each channel's faults. The authentic data with no faults in each channel is released for output. With 2oo2 logic, the alarm is activated without displaying the data if there are faults in both channels. However, if a fault is detected only in one channel, the system reverts to the safe 1oo1 channel and continues to operate without interruption to record the data set. This way, the alarm and data calculation values are generated and recorded. These resulting values are

displayed for each channel, ECG-1oo1 & PCG-1oo1, along with 2oo2 resulting operating modes for examinations.

3.6 Methodology

The experimental activities of this research project are divided into mainly three main parts:

- The first part is dedicated to evaluating the aptness to use safety-related architectures in medical systems to measure basic vital parameters and identify suitable sensors for sensing biomedical signals like sensing thru electric potential, sound, and light.
- The second part is dedicated to the design and realization of three-independent channels with sensor and FPGA-based research prototypes for experimental studies.
- The final part is dedicated to the calibration of the research platform (sensor, configurable safety architectures, and FPGA circuits) by performing lab and field trials in evaluating the vital parameters like heart rate in addressing the mentioned challenges such as reduction of fault alarms, algorithm limitations, and uninterruptable functionality with safe degradation.

3.7 Fault-tolerant System Prototyping and Experimental Analysis

3.7.1 System Overview

The system is designed in a modular approach, and each device unit consists of a Field Programmable Gate Array(FPGA) and an analog front-end(AFE) device. The flexibility in this approach is used to configure the device in any of the proposed safety architectures for safe, functional computations in diverse methods.

A system block diagram in

Figure 13 has three independent, diverse channels of Device-A, -B & -C, and voting logic output in Device-O. The system operates at 100 MHz, and each channel processes a single data type of multi-input signal. For example, an ECG signal is based on electrical sensing data type, a PPG signal is based on optical sensing data type, and a PCG signal is based on sound wave sensing data type. Each device -A, -B &-C has an FPGA XC6SLX45 and an analog front-end(AFE), and device – O uses an FPGA having a controller with 16MB flash memory and

64MB dynamic RAM that processes the voting logic and interacts with GUI. The CHMS GUI is a front-end software tool developed in MATLAB, which controls and interacts with the system via a high-speed serial interface. The CHMS GUI is a multipurpose tool operated from a PC and can be utilized for real-time analysis of the received sensor sample data from three different channels.

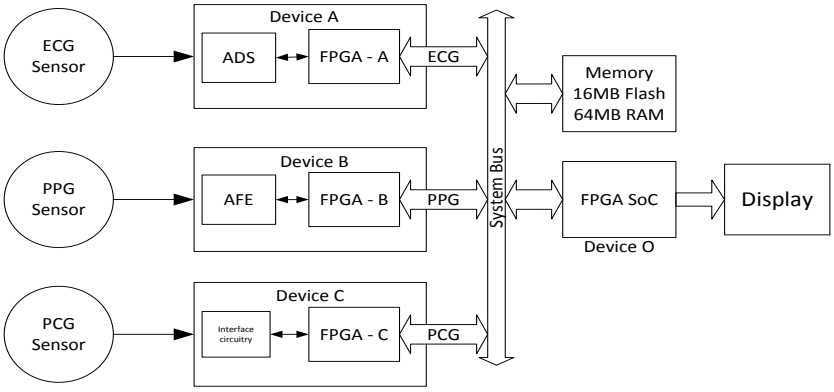
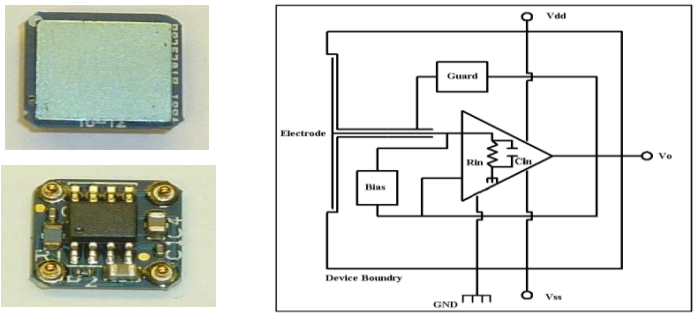


Figure 13: HHMS -System Block Diagram.

3.7.2 Device A– ECG signal computation channel design (ECG System)

Overview: Device -A is an independent ECG signal processing channel. This device consists of a Sensor, AFE, and FPGA module.

EPIC Sensor: Using a capacitive sensing technique, the present system uses an electric potential integrated circuit (EPIC) sensor chip, a non-contact or dry contact sensor, to sense the electro potentials on the skin's surface. This advanced sensor chip acts as a near-perfect electro-voltmeter. It eliminates the effects on the subject or patient, shaving the hair on the skin, using gels, and other contact-enhancing substances. It is a perfect suitable sensor for this type of portable/wearable CHMS application measuring the ECG since there is no need for potentially dangerous low impedance circuits across the heart. The availability of sensor resolution is as good as or better than conventional wet electrodes.

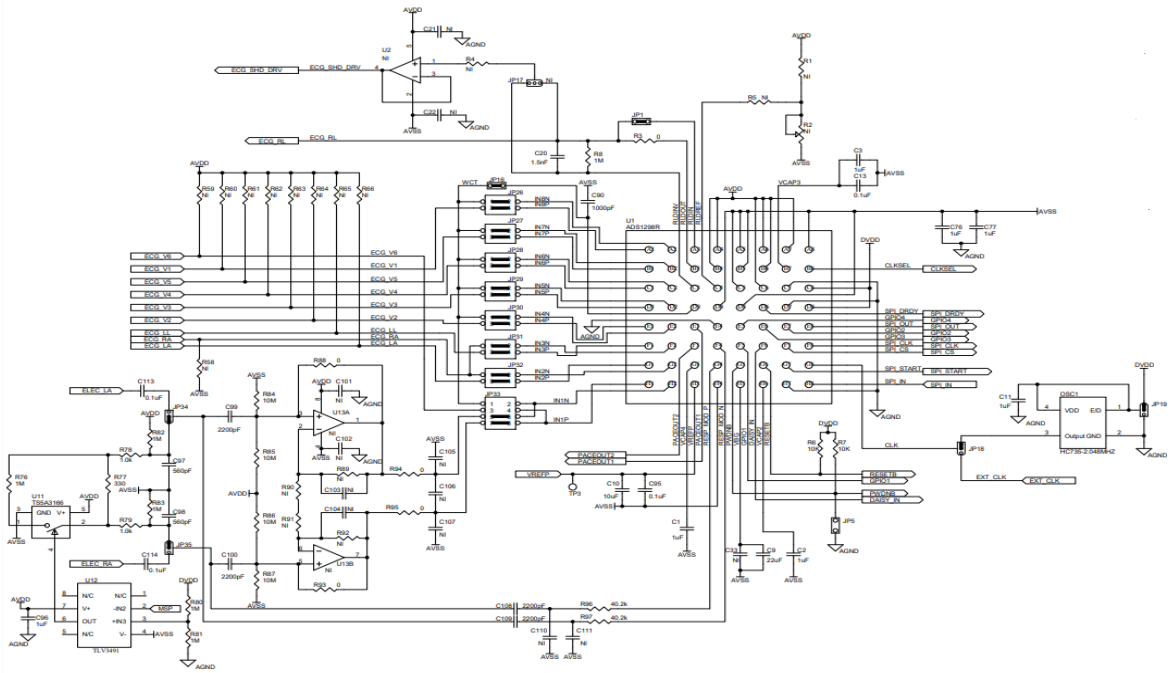


(a) (b)

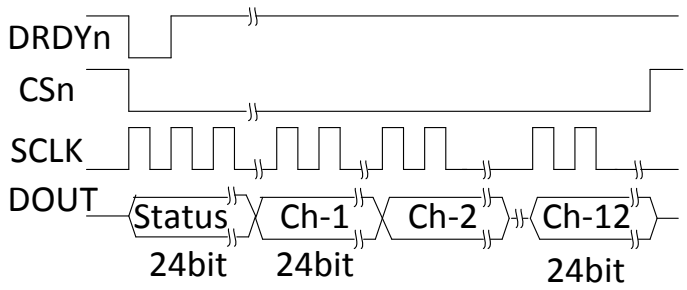
Figure 14: (a) EPIC Sensor, Courtesy of photo from Plessey Semiconductor sensor datasheet, and (b) Internal sensor schematic.

A single EPIC sensor, when placed on or near the patient, an ECG signal can be recovered and is capable of monitoring continuous ECG as well as making more exacting clinical diagnostic measurements. An array of EPIC sensors, placed on the chest in a traditional 12-lead configuration position, can recreate the signal resolution as good as or better than the one achieved using traditional electrodes. These EPIC sensors can diagnose various heart diseases, measured and interpreted through ECG recordings.

Two EPIC sensors are used, and the outputs are connected to the pins of ADS1298R chip 1NN & 1NP in differential, i.e., connected to ADC channel-1. In contrast, the chip is configured in a differential mode of operation.



(a)



(b)

Figure 15: (a) Circuit Schematic ADS1298R of Device-A (Ref. TI) and (b) SPI Protocol for data sample reading.

Analog Front-End(AFE): The device uses an analog front-end AFE1298R chip from Texas Instruments, and it can be used to acquire biopotentials such as 12-lead ECG signals or EEG signals. The chip has low-power eight-channel, 24-bit-delta-sigma (ΔΣ) analog-to-digital converters (ADCs) with built-in programmable gain low noise amplifiers(PGAs) with simultaneous sampling functionality.

The device is configured to obtain 1000 Samples per second (SPS) and is interfaced with two electric potential integrated circuit (EPIC) sensors in differential mode. First, FPGA configures the AFE device via the SPI interface in reading Data Continuous (RDATAC) mode. It reads data continuously in an 8-bit burst cycle, such that all 216 bits per device (24 status bits + 24 bits per channel) X 8 channels). Next, an FPGA reads an additional second AFE device interface in daisy chain configuration for an additional 4-channels via SPI interface. A highlighted schematic and SPI data timings are shown in Figure 14 and Figure 15.

ECG Data Pre-Processing using FPGA: An FPGA is used to perform the desired computation of measuring the heart rate by detecting R-peaks in real-time from the received ECG data collected from a subject or a patient.

On power-up, the GUI configures the FPGA for the desired functions to perform. The designed FPGA consists of an ECG controller, SPI controller, and ECG function-specific IP cores, as shown in Figure 16. Once configured by the GUI, the ECG controller coordinates by configuring the AFE ADS1298R, and they start reading the ECG data via SPI. Then, based on the desired function set by GUI, the ECG controller uses a specific function IP core. Finally, this algorithm is enabled in the ECG processing Engine (EPE) and sends the measured values to Device –O for safe correlation logic.

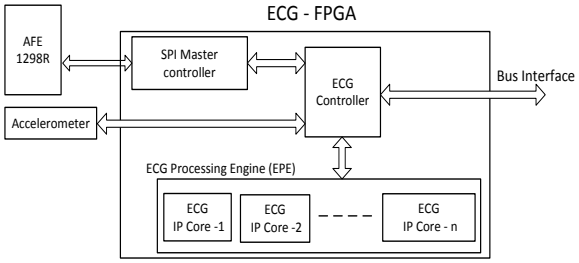


Figure 16: ECG-FPGA for function computation.

This proposed system performs an R- peak detection function computation on every 1000 samples per second (SPS). First, the sampled ECG data is continuously received for a defined period, configured via GUI. Then, the detected R-peak count values are processed to measure the heart rate, and this parametric data is correlated using a safe function in Device –O.

R- Peaks detection: Detection of the QRS complex is essential to detect the R-peaks. The algorithm in [208] has successfully detected QRS with an accuracy of 99.5% using single-channel ECG with entropy criteria. This algorithm is implemented in the present work for heart rate measurement.

3.7.3 Device B– PPG signal computation channel design (PPG System)

Overview: Device -B provides an independent channel to process the photo-plethysmogram (PPG) signals. This device consists of a Sensor (LED and Opto-detector), AFE, and FPGA module.

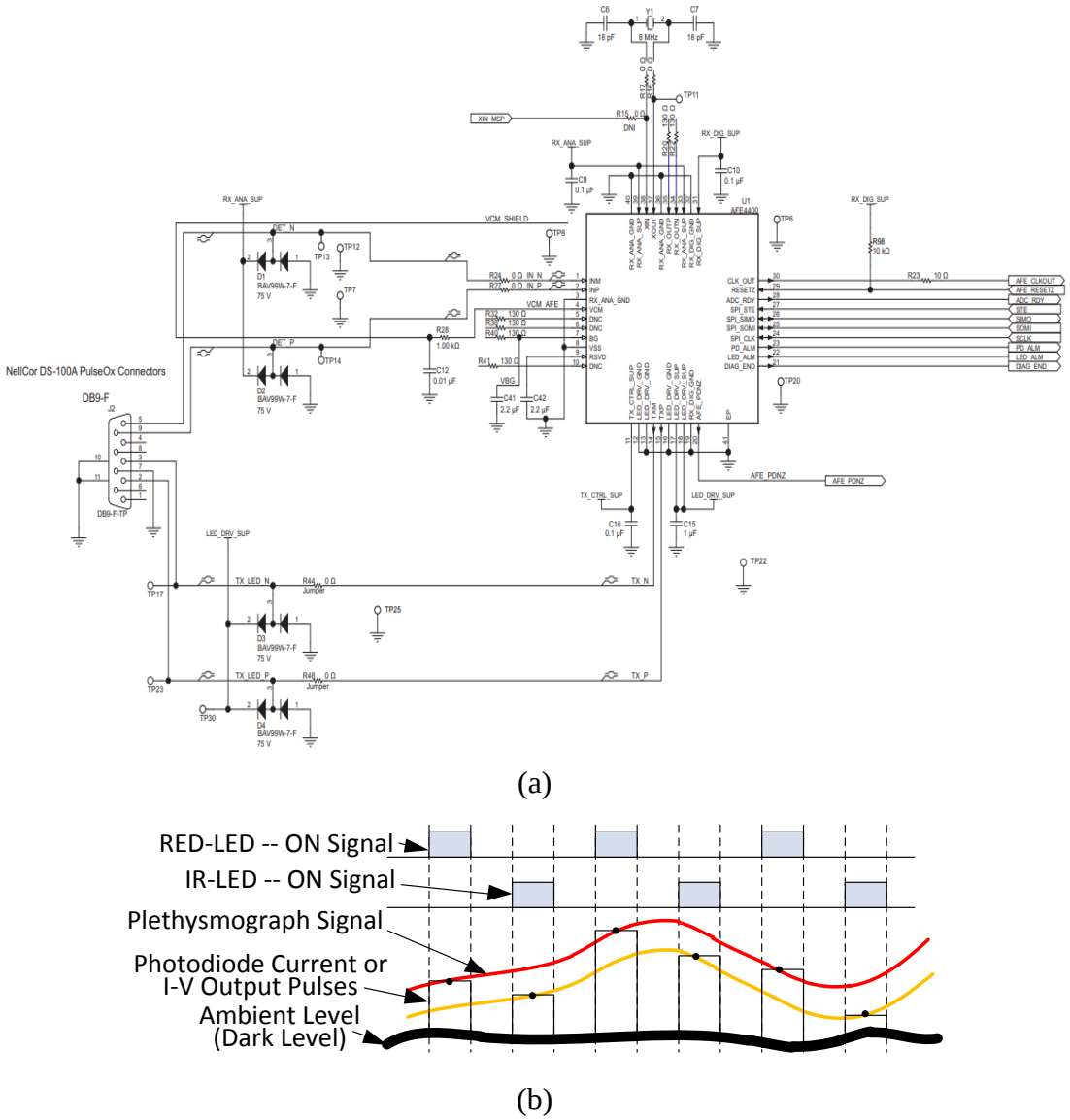
PPG sensor and detector: PPG is an optically obtained volumetric measurement of an organ. In principle, PPG is measured by illuminating the skin and subcutaneous tissue with radiation of a specific wavelength. This radiation will come from a light-emitting diode (LED). When illuminated at a patient's measuring point, the capillaries under the skin absorb, transmit, or reflect the light. Depending on where it is in relation to the LED, a photodiode can sense either the light being sent through or the light being sent back. The photodiode then converts the measured light into an electrical signal.

In this system, we used two LED sources of specific light wavelengths-- red, 660 nm, and infrared, 940 nm. For the photodetector, we used OP101 IC to detect the transmitted light.

Analog Front-End (AFE): An AFE4490 chip is used in the device -B. This chip is a fully-integrated analog front-end (AFE), ideally suited for pulse-oximeter applications. In addition, this device is suited for measuring heart rate and other blood parameters. The device consists of a

low-noise receiver channel with a 22-bit analog-to-digital converter (ADC), an LED transmit section, and sensor and LED fault detection diagnostics.

The device is configured to process 200 Samples per second (SPS) and is interfaced with FPGA. FPGA configures the AFE device via the SPI interface and reads data continuously for further processing. A highlighted schematic and sample data timings are shown in Figure 17.



(a)

(b)

Figure 17: (a) Circuit Schematic of AFE4490(Ref. TI) of Device-B, (b) Sample data read timings.

PPG Data Pre-Processing using FPGA: The PPG-FPGA sub-system performs the desired computation, like measuring the heart rate by detecting P-peaks in real-time from the received PPG data collected from a subject or a patient via an AFE SPI interface.

On power-up, the FPGA is configured by the graphical user interface (GUI) for the desired functions. The designed FPGA consists of a PPG controller, SPI controller, and PPG function-specific IP cores, as shown in Figure 18. Once the GUI configures, the PPG controller coordinates by configuring the AFE4490 and starts reading the PPG data via SPI. Then, based on the desired function set like heart rate by GUI, the PPG controller enables the specific IP core (where a specific algorithm is executed) in the PPG Processing Engine (PPE) and sends the measured values to the Device-O for safe correlation logic.

A P- peak detection function computation is performed on every 200 SPS. The sampled PPG data is continuously received for a defined period, configured via GUI. The detected R-peak count values are processed to measure the heart rate, and this parametric data is correlated using a safe function in Device –O. The functional block diagram of the PPG-FPGA implemented logic is shown in Figure 18.

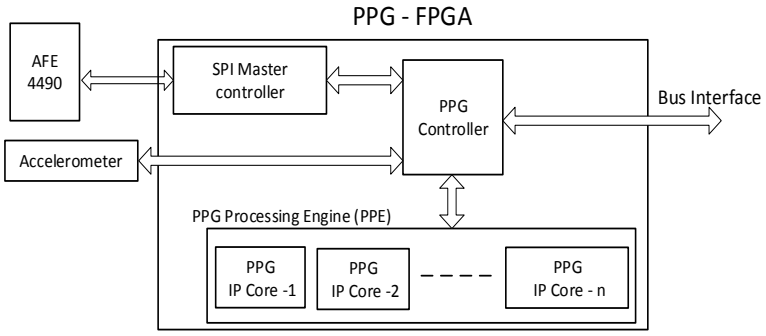


Figure 18: PPG-FPGA for function computation.

P- Peaks detection: Each cardiac cycle sends a pressure wave through the cardiovascular system. This pressure wave causes the blood vessels to expand and contract, which gives the PPG a characteristic waveform. Since the period of the PPG waveform repeats with each cardiac cycle, it, too, can be used to calculate a patient's heart rate.

The algorithm in [207] has successfully detected the pulse rate with an accuracy of 99.39% using PPG with entropy measures. This algorithm is implemented in the present work for heart rate measurement.

3.7.4 Device C– PCG signal computation channel design (PCG System)

Overview: Device -C is an independent channel to process the Phonocardiogram (PCG) signals. This device consists of a Sensor (Digital MEMS microphone) and an FPGA module.

PCG sensor: The device uses four individual Digital MEMS microphone MPDT01 sensors, and each sensor covers the four heart valves (Aortic, Tricuspid, Mitral, and Pulmonary). The criteria for selecting this sensor are low noise, miniaturized device, low cost, and simple interface to process the binary sound signal. The digital MEMS microphone has a digital output type of Pulse Density Modulation (PDM) format, with a high sensitivity of -26 dBFS, signal-to-noise ratio (SNR) of 62.6 dB, and a flat frequency response of 20 Hz to 15 kHz. The set of sensors is placed on the human chest to capture the heart sounds at four heart valves simultaneously with good quality due to its high sensitivity and flat frequency response.

The digital MEMS chip has an inbuilt signal preconditioning, filtering, and signal enhancement module that provides digital PDM output for further processing in an FPGA. The sensors are interfaced serially to FPGA and capture the data at 1 MHz in line with the data read timings specified in the MPDT01 datasheet. The highlighted interface circuit schematic and its data read timings are shown in

Figure 19.

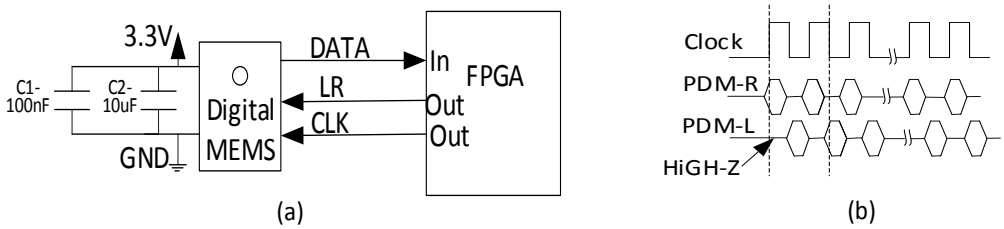


Figure 19: (a) Device-C Circuit and (b) Data read timings.

PCG Data Pre-Processing using FPGA: The PCG-FPGA performs the desired computation, like measuring the heart rate by detecting S-peaks in real-time from the received PCG data.

On power-up, the GUI configures the FPGA for the desired functions to perform. The designed FPGA consists of a PCG controller, which enables the PCG processing engine (PCE) to capture and process the received digital data from the MEMS, as shown in Figure 20. Based on the desired function set like heart rate by GUI, the PCG controller enables the specific IP core

(where a specific algorithm is executed) in the PCG Processing Engine (PPE) and sends the measured values to the Device-O for safe correlation logic.

An S- peak detection function computation is performed on a 2000 SPS. The converted PDM to PCM sampled PCG data is continuously received for a defined period, configured via GUI. Then, the detected S-peak count values are processed to measure the heart rate, and this parametric data is correlated using a safe function in Device –O.

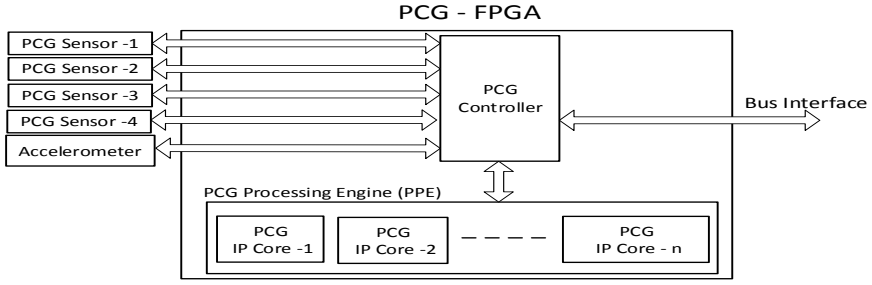


Figure 20: PCG-FPGA for function computation.

S- Peaks detection: At each cardiac cycle, major heart sounds S1 and S2 are produced due to the closing and opening of the heart valves. The heart rate is directly proportional to the number of S1 peaks per minute, so S-peaks detection is considered for heart rate monitoring.

The algorithm in [224] has successfully detected the S1 peaks using spectral analysis of PCG data and measuring the number of S1 peaks per minute. This algorithm is implemented in the present work for heart rate measurement.

3.7.5 Device O -Safe-selection logic implementation using Karl Pearson's correlation coefficient method

To measure the magnitude of the relationship between two variables, [136][137][138][139] we used the Karl Pearson coefficient method for calculating the correlation coefficient 'r.'

$$r = \left(\sum XY\right) \Big/ \sqrt{\left(\sum X^2 \times \sum Y^2\right)} \quad (1)$$

$$X = x - \bar{x} \quad (2)$$

$$Y = y - \bar{y} \quad (3)$$

where $\bar{x}$, $\bar{y}$ are "mean."

The 'r' values always lie in between -1< r < 1, and the interpretation of 'r' is as below:

When r = 1, the variables have a perfect +ve relationship. When r = -1, there is a perfect -ve relationship between the variables, and when r = 0, there is no relationship between the variables.

Moreover, if the correlation is +1 or –1, it signifies a high degree of correlation. (+ve or –ve) between the two variables. So, if r is near zero, i.e., 0.1, -0.1, (or) 0.2, there is less correlation.

As a rule-of-thumb for interpreting the coefficient of correlation value 'r,' below Table 5 shows the standard interpretation of the relationship between two variables.

The measured variables A and B from two diverse signals are correlated, and the correlation coefficient 'r_{AB}' is calculated in a set of pre-determined continuous samples.

Table 5: Rule of Thumb to interpret the correlation coefficient 'r' values.

Coefficient of Correlation 'r'	**Interpretation**
0.90 to 1.00 (-0.90 to -1.00)	Very high +ve or -ve
0.70 to 0.90 (-0.70 to -0.90)	High +ve or -ve
0.50 to 0.70 (-0.50 to -0.70)	Moderate +ve or -ve
0.30 to 0.50 (-0.30 to -0.50)	Low +ve or -ve
0.00 to 0.30 (-0.00 to -0.30)	Negligible

3.7.6 Assessment of Reliability of the Instrumentation System

In this experimental evaluation, emphasized that the reliability is the ability of equipment to function without failure. Reliability is closely related to availability, which is typically described as the ability of a component or system to function at a specified moment or interval of time. During the experiment, the assessment is performed on the recorded data sets with timestamps and the number of failures.

Mean time between failures (MTBF) is measured by measuring the elapsed time between inherent failures during normal system operation. MTBF can be calculated as the arithmetic mean (average) time between failures of a system. The term is used for repairable or redundancy systems, while mean time to failure (MTTF) denotes the expected time to failure for a non-repairable or negation system.

$$MTBF = \frac{\sum(start\ of\ downtime - start\ of\ uptime)}{(Number\ of\ Failures)} \quad (4)$$

Similarly, mean downtime (MDT) can be defined as

$$MDT = \frac{\sum(start\ of\ uptime - start\ of\ downtime)}{(Number\ of\ Failures)} \quad (5)$$

Where 'Uptime" is the time between two failure states
"Downtime" is the instantaneous time it went down, which is after the moment it went up

$$MTBF = \int_0^\infty R(t)dt = \int_0^\infty tf(t)dt \quad (6)$$

Where $R(t)$ is the reliability function, which can be expressed as the expected value of the density function f(t) of time until failure

$$f(t) = \lambda e^{-\lambda t} \quad (7)$$

Where λ, is the constant failure rate of the system

$$MTBF = \frac{1}{\lambda} \quad (8)$$

Where MTBF is the expected value, average, or mean of the exponential distribution

In a quantitative analysis, repeatability and reproducibility parameters are considered for instrument reliability performance assessment.

3.8 Case study: Results Analysis and Discussion

The processed data and fault alarm signals are captured from channels ECG-1oo1 and PCG-1oo1, and configured 2oo2- outputs are presented in Figure 21, Figure 22, and Figure 23 for a single subject. As it is analyzed, the reading from all fifty subjects is almost similar, and Figure 24 presents the 2oo2- results, which show the reduction in alarms.

Figure 21 presented the data captured from ECG 1oo1 channel with HR measured data and inverted alarm signal for 1 hour. Analysed and captured alarms with respect to the set ADJ-UL & LL are shown. Similarly, for the PCG 1oo1 channel shown in Figure 22.

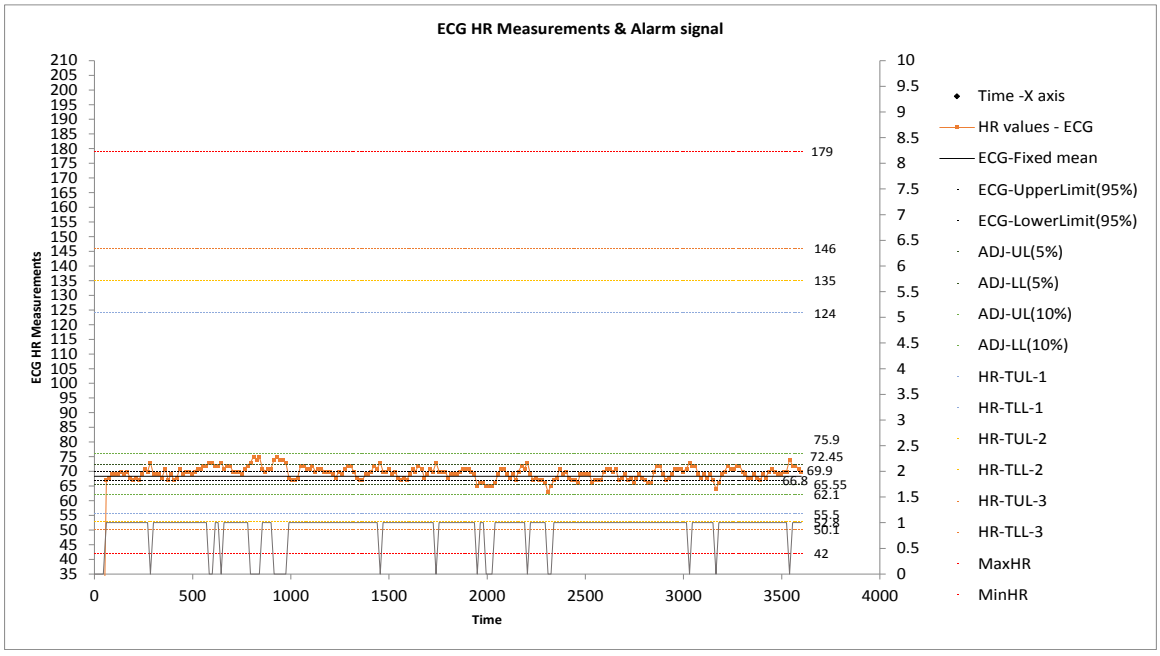


Figure 21: 1oo1 -ECG HR measurement Vs. Alarm Signal.

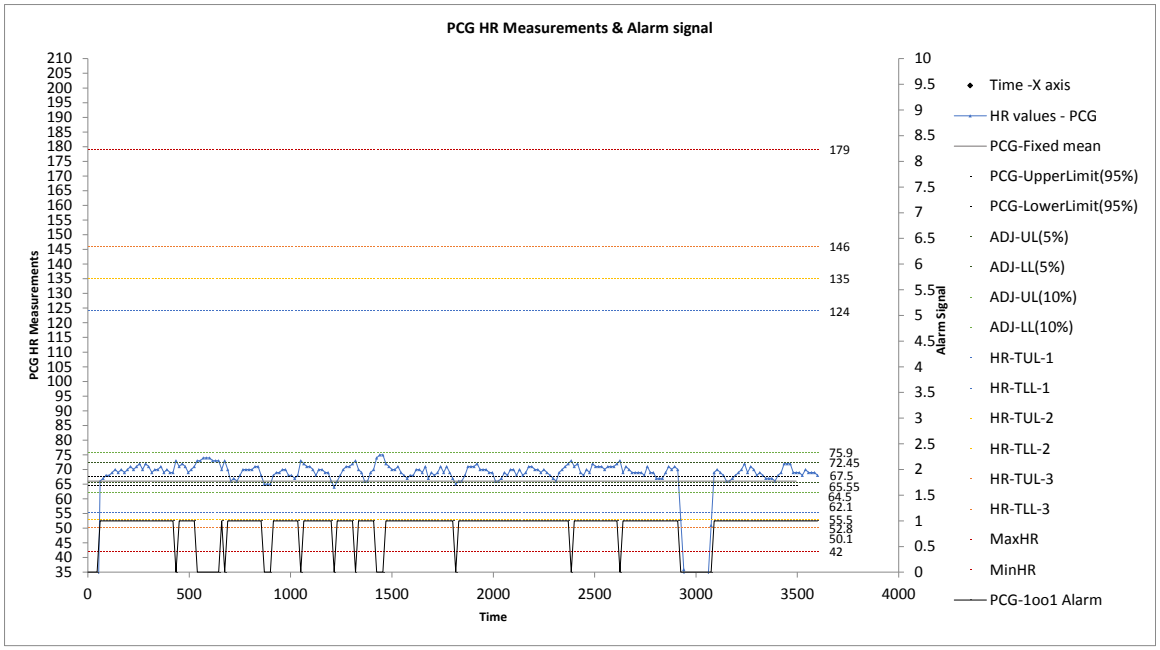


Figure 22: 1oo1 - PCG HR measurement Vs. Alarm Signal.

The correlation coefficient 'r_{AB}' values and the ECG and PCG HR measurements are captured in Figure 23 and analyzed for deviances at each channel.

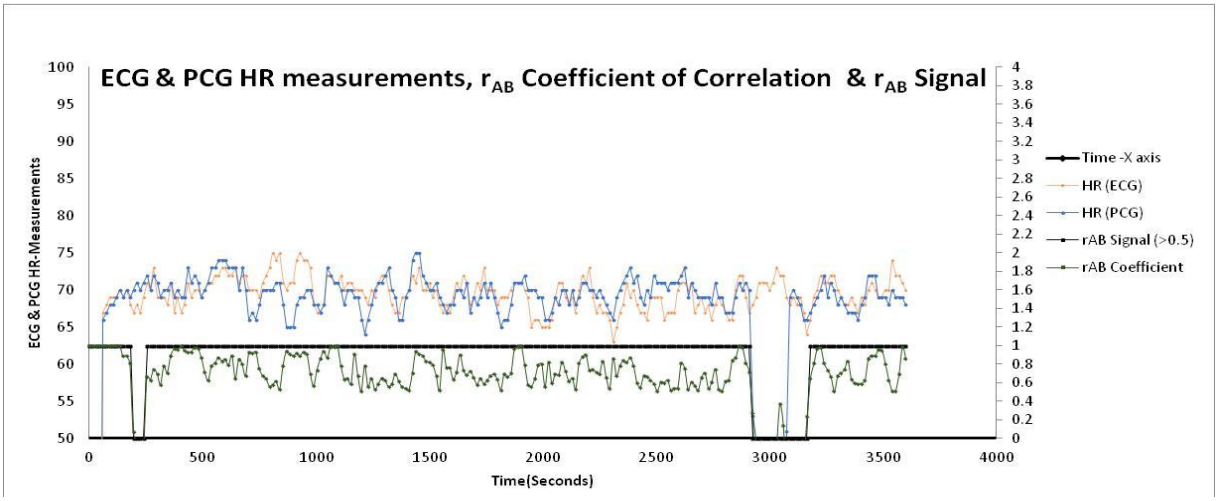


Figure 23: ECG & PCG HR measurements, r_{AB} Correlation Coefficient values Vs r_{AB} Signal.

The comparative and safe logic degradation and its implementation analysis using alarm signals are captured in Figure 24, which shows a significant reduction of alarms with consistent HR data records in the 2oo2 design architecture.

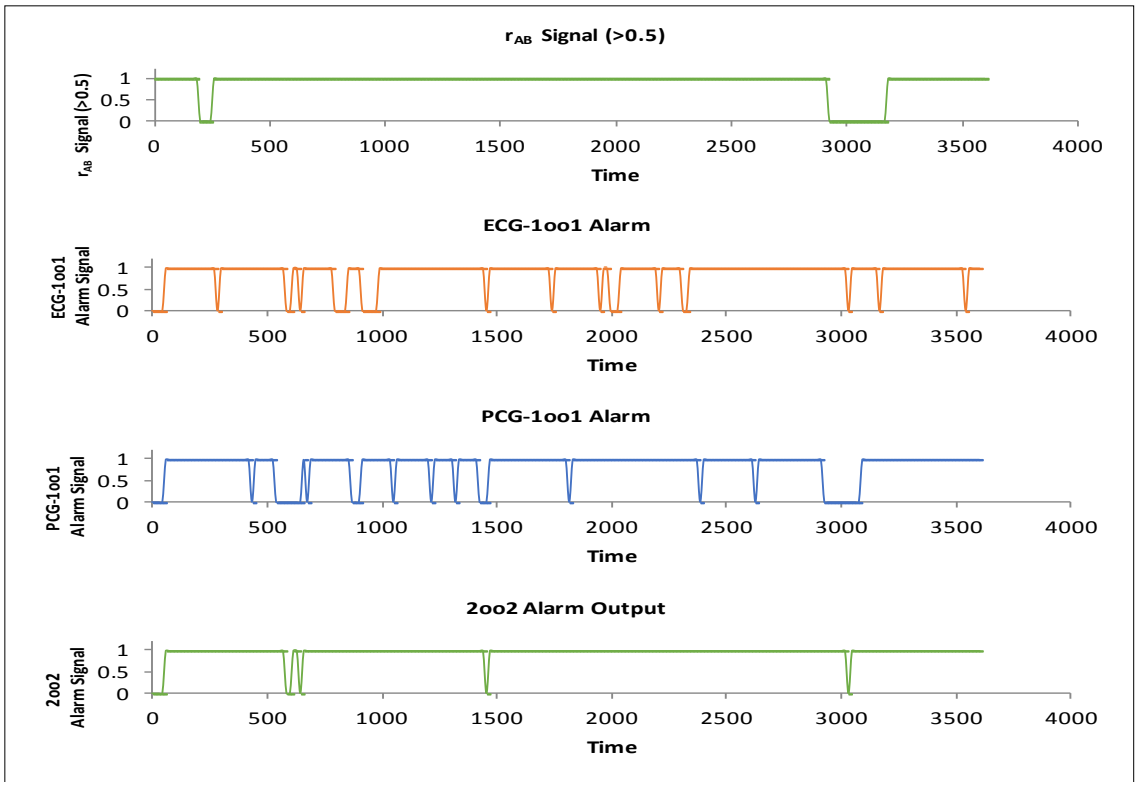


Figure 24: r_{AB} Signal and Alarm outputs (ECG -1oo1, PCG -1oo1, and 2oo2 configured Alarm signal).

Furthermore, though the data collected from the three independent channels during the experiment, the data is analysed in detail in 2oo2 configuration. However, a high-level data analysis on 2oo3 architecture configuration is presented below Figure 25, which shows more significant reduction in the spurious alarms but highlights limitations in the synchronization issues between the channels during data capture.

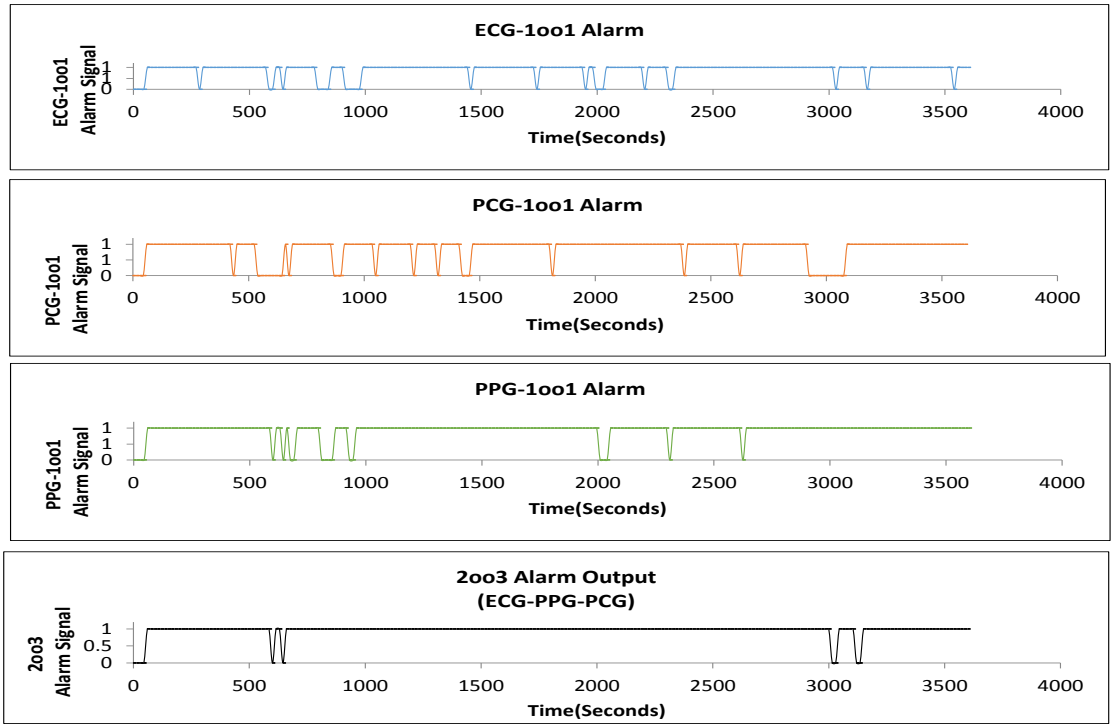


Figure 25: Alarm outputs (ECG -1oo1, PCG -1oo1, PPG – 1oo1 and 2oo3 configured Alarm signal).

Table 6: CHMS Operational Availability and MTBF Results

Configuration Type	Sensor channel	Up-time [Avg. minutes] ['t' - 60 minutes]	Down-time [Avg. minutes] ['t' - 60 minutes]	Number of Failures	System Availability	System Availability [Avg of 200 Hrs]	MTBF [~ minutes]	MTTF [~ minutes]
1oo1 (Using ECG Simulator with 60 BPM set)	ECG1	57.2	2.8	4	95.33%	96.00%	13.6	13.6
1oo1 (Using ECG Simulator with 60 BPM set)	ECG2	56.4	3.6	6	94.00%	95.00%	8.80	8.8
1oo1	ECG1	48.2	11.8	11	80.33%	84.00%	3.31	3.31
1oo1	ECG2	49.6	10.4	6	82.67%	83.00%	6.53	6.53
2oo2 (Using ECG Simulator with 60 BPM set)	[ECG1-ECG2]	55.8	4.2	3	92.67%	93.75%	17.20	Not Applicable for repairable systems
2oo2	[ECG - PCG]	54.6	5.4	2	91.00%	94%	24.60	
2oo3	[ECG - PCG - PPG]	58.4	1.6	3	97.33%	99.10%	28.40	

Further, the CHMS is evaluated for reliability using ECG simulator as well as experimented practically on subjects over and above 200 subjects, by measuring the System level Availability, MTBF, Repeatability, and Reproducibility parameters. Table 6 shows the result of higher MTBF value of 28.40 for -2oo3, showing improvement in availability from the -1oo1 and -2oo2 system, and similarly from a single channel systems. Following the application protocol, experimental system evaluation is performed for repeatability and reproducibility. Table 7 shows that the measured repeatability reproducibility values have less variance when compared to the 1oo1 and -2oo2 systems. However, the considered limitation is complexity and synchronization issues, which increases further in -2oo3, and by following a systematic design approach and guidelines may further help in the reduction of the limitations in complexity.

Table 7: CHMS Repeatability and Reproducibility Results

Configuration Type	Sensor channel	Repeatability of CHMS (SD)	Repeatability of CHMS (SDM)	Reproducibility of CHMS
1oo1 (Using ECG Simulator with 60 BPM set)	ECG1	2.18	0.69	0.0707
1oo1 (Using ECG Simulator with 60 BPM set)	ECG2	1.90	0.60	1.6263
1oo1	ECG1	2.16	0.68	0.07
1oo1	ECG2	1.52	0.48	1.63
2oo2 (Using ECG Simulator with 60 BPM set)	[ECG1 - ECG2]	1,90	0.60	1.6263
2oo2	[ECG - PCG]	1.70	0.54	0.79
2oo3	[ECG - PCG - PPG]	1.20	0.38	0.1414

3.9 Conclusion

Continuous monitoring of patient vitals with minimized false alarms and correct reporting of measured vital data is essential for any critical patient monitoring system, regardless of potential problems. During patient monitoring in the ICU or during regular patient inspections, it is more crucial for critical care nurses to properly forecast the presence of illness than at other times.

The current research project is related to evaluating safety design architectures with and without redundancies and their aptness usage in designing fault-tolerant, non-invasive medical systems. Detailed literature has been reviewed in medical systems like patient monitoring

systems, point-of-care medical devices, and related available functional system specifications for processing non-invasive biomedical signal processing preceding the current research to approach these challenges most appropriately. At this point, we believe improving the medical system's resiliency is possible by applying safety-related design approaches. We build a prototype of a multimodal wearable sensor suite and an FPGA-based medical diagnostic system.

The preliminary experiments have been conducted using this prototype with 2oo2 safety architecture configuration with ECG & PCG sensors and measured the HR to understand the cardiac physiology. The initial recordings and analysis results are encouraging, with uninterruptable and authentic HR data and reduced alarms. Further, the measured MTBF results for CHMS show improvement in reliability in 2oo3 configuration and less variance in results of repeatability reproducibility compared to 1oo1 and -2oo2 systems.

Furthermore, with this experimental setup, we extend to configure the CHMS system with 1oo2-, 2oo2, and 2oo3 settings and perform research experiments to collect the data. It serves us to study further the correlative analysis of non-invasive biomedical signals on measured parameters in combination with pathological data to infer predictable and early detection of unknown illnesses along with mitigating the desired challenges.

Chapter 4. Development and Optimization of Fault-tolerant Human Health Monitoring Systems based on 2oo2 Architecture

4.1 Overview

Human Health Monitoring Medical Systems (HHMMS) are advancing at a dramatic rate, bringing safety improvements by aiming to deliver improved quality and accuracy in predicting disease, faster diagnostics, and user-friendly interfaces [134][190][191][192][193]. With advancements in technology, there is a scope to address the present challenges in the identification and detection of the actual abnormal vital (heart-rate) cardiac signal [194][195]. Most of the existing non-invasive medical systems [139][196][197][198] use 1oo1 (one-out-of-one) system architectures. i.e., one sensor measures one or more vital health parameters, generates an alarm as per safety severity level if any disturbance occurs, and halts system functional operation if the severity level is high [118][199]. This type of non-invasive medical monitoring device is often subject to insignificant failures with potentially catastrophic impacts on patients. A study [113] of medical device recalls between 2006 and 2011 shows a 69.8% increase in product recalls and a 103.3 percent increase in the number of adverse events to patients, like improper medications and deaths, where most of the recalls are due to the cause of software faults. In a recent report [117] for 2018, a significant spike of 126% increase in product recalls informed the Food and Drug Administration (FDA) of the U.S. that most of the causes are due to software faults. The shortage of these features in identifying and detecting an abnormal signal may cause improper data analytics and incorrect prognostic health diagnostics, leading to improper nursing.

In this chapter, we focused on improving the safety feature of the detection and identification mechanism of actual normal and abnormal vital heart signals. In realizing this safety feature, a detailed framework proposed to use [200] a 2oo2 (two-out-of-two) configurable safety design architecture based on the composite fail-safety technique is evaluated by implementing the safety feature. Furthermore, the segregated vital (heart-rate) logged normal and abnormal data is analyzed using the AI method. Thus, the logged results are analyzed and tabulated for prognostic health diagnostics performance towards inferring the health of the

cardiac as healthy and not healthy, which further helps in the proper assessment of the patient's condition and supports appropriate nursing.

The implemented safety feature helps accurately segregate normal and abnormal vital signals. Further, the captured normal and abnormal data is plotted for visual analysis apart from prognostic analytics. The extended research scope may utilize the segregated data for further signal analytics to extract accurate signal artifacts and histopathological data for pathological completeness.

Sections 4.2 and 4.3 detail the background and motivation and provide details about the framework to address the challenges using the improvement feature mechanism. Section 4.4 provides a methodology in detail about the system overview and details the current research phase towards improvements in the safety-related 2oo2 design with two independent and diverse channels for experimental evaluation studies. Finally, in Section 4.5, a detailed discussion of the experimental results and further application of this approach to other vital parameters emphasized improvements in authentic detection and prognostic health diagnostics.

4.2 Safety-related Fault-tolerant 2oo2(two-out-of-two) design Conceptualization Analysis

4.2.1 Related work and motivation

The design of medical systems towards more accuracy and resiliency is quite challenging, and to mitigate this, in the recent past decade, developed and used a few techniques like data fusion techniques[133][134][138][190][199], Artificial Intelligence-based techniques [136][138][201] [202][203][204][205] and correlation techniques [139][196][197][205][206]. However, All these techniques will have limitations and fall short of addressing the issues. The issues include accurate identification and separation of appropriate signal data for data analytics to extract artifacts, identification of inaccurate signal data, and determining the root cause of faults such as systemic or random failures to determine the health of medical systems. In addition, in-depth studies [118] [133][194][198][199][206] show that potential faults in sensors or related system design factors may cause the bio-signal to be embedded with external environmental faults.

In the recent past, studies reported that the same vital parametric data, like heart rate, can be realized with different mediums of the sensor [133][136][139][197]. These studies motivate us to improve an additional safety feature in our fault-tolerant safety-related design research platform,

CHMS. Therefore, we used [200] the research platform and configured it to 2oo2 with a safety aspect in effectively identifying and segregating the signal data from the various faults. The presented framework provides an approach and the implementation results using the configurable safety-related 2oo2 design architecture.

4.3 A framework for Safety-related 2oo2 system and its evaluation

The primary medical monitoring system design aims to sense the bio-medical signal accurately. However, if the signal is sensed, detecting the actual informative signal is more important from the various disturbing factors like high noise signal interference, electronic and software faults, mechanical faults like sensor contact failures, and equipment wear and tear.

Identifying and detecting abnormal signals required more focus areas in the design of present medical systems. Hypothetically, the accurate data and data analytics based on AI methods give more accurate vital parameter measured values, which helps perform better nursing and predict diseases. To mitigate the above challenges and achieve improved identification and detection, we proposed a framework to use the 2oo2 (two-out-of-two) safety-related architecture configuration and use different sensors, PPG, and ECG for evaluation.

4.3.1 Configurable 2oo2(two-out-of-two) Design Architecture

The research platform [200] was configured to 2oo2 with diverse sensors interfaced to each independent channel. The vital parameter cardiac signal is selected, and measured heart rates are used for experimental evaluation of the implemented safe improvement function. The ECG and PPG signal processing validated algorithms [200] are used in measuring the heart rate independently at each independent channel. Further, the safety principles and conditions followed as mentioned:

- The composite fail-safe principle is used and followed in a 2oo2 design that needs to adhere, i.e., each channel is self-compared and voted against the other channel.
- The safe voting mechanism is, in principle, a parallel circuit. i.e., the system goes into fail-safe when both conditions need to fail.
- Both conditions, safe parameter boundary limit and positive correlation of parameters, should be true.

- Continuous Built-in-Test functions monitored for the identified hardware and software cases of systemic and random failures should not fail. Instead, the system goes to the fail-safe state.

An AND-OR safe function is implemented to generate the fault signal to trigger the normal and abnormal signals. These signals are captured using the CHMS GUI tool and display PPG and ECG signal abnormalities. Thus, the captured signals and logged data are further subjected to prognostic data analysis to provide more accurate inferences for the desired disease settings. Furthermore, the determination of accurate inferences is further enhanced by including the histopathology data for completeness. Thus, the mentioned challenge is mitigated and provides resourceful inference data for better nursing.

4.3.2 Evaluation Framework

We used a verified [207] fuzzy entropy-based detection and estimation algorithm to process the PPG signal and perform data analytics. We used the calculated modified entropy measure as below:

$$H\left(A_{n,k,\lambda}^{\lambda}\right) = \mathrm{F}\left(\sum_{i=1}^{2k} h\left(A_{n,k}^{\lambda}\left(x(n)\right).\Delta x_i\left(n\right)\right)\right) \quad (1)$$

$$where\ member\ function\ is = A_{n,k}^{\lambda}\left(x(n)\right) = ppg(n_1 : n_2)$$

$$\Delta x_i\left(n\right) = x_{i+1}(n) - x_i(n);$$

Similarly, we used a verified [208] fuzzy neural signal processing system to determine the R-peaks for processing the ECG signal and performing data analytics. The performance of the algorithms for identifying accurate pulses observed during normal and abnormal segregated logged data using positive predictive values (PPV) and sensitivity (Se) parameters is defined as follows, and calculated values are tabulated.

$$Sensitivity = \frac{t_p}{t_p + f_n}; \quad (2)$$

$$Positive\ Predictive\ Value = \frac{t_p}{t_p + f_p};$$

$$where\ t_p\ is\ True\ positive,$$

$$f_p\ is\ false\ positive,$$

$$f_n\ is\ false\ negative$$

Thus, MATLAB-based CHMS GUI helps capture the data pictures and signals during the one-hour duration, thus providing a visual option for visual inspection of the desired signal captured data. Thus, this framework may help appropriately address the challenge of identifying the actual abnormality of the vital cardiac signal.

4.4 Design Methodology

As part of the three-phase experimental research activities in the realization of the safety-related medical monitoring system, we reused [200] system prototype realized in phases 1 and 2 and worked on the safety improvements in the final phase of the research activity.

In this final phase, the experimental research platform was used to validate one of the focused improvement concepts of accurate segregation of normal and abnormal cardiac vital signals for performing data analytics and prognostic health diagnostics and providing accurate inferences on cardiac health. As a broader scope, the system was evaluated with varied configurations with elements such as PCG, ECG, PPG sensors, configurable safety-related architectures, and FPGA device-associated circuits. We are performing lab and field trials to assess the safety improvement function and provide factual inferences on detected abnormalities of cardia health vital measured parameters.

In the present research evaluation setup, we configured the existing platform in 2oo2 safety-related design architecture with two independent channels, having interfaced with two different sensors, PPG and ECG. As a case study, we evaluated the safety improvement function using these two different PPG sensors and ECG, along with diverse signal algorithms used for evaluation. However, the system needs to evaluate further combinations of PPG-PPG, ECG-ECG, PCG-PCG, or any other cross combinations for completeness.

4.4.1 Safety System Overview

The medical system called the CHMS is designed to be modular and configured to a 2oo2 safety-related computing platform. The safety-related system mainly consists of two independent operating channels, as shown in *Figure 26* and explained in [200] detail, with CHMS GUI interfaces for data collection and analysis.

The sensors used for ECG and PPG are detailed in [200], and the selected vital is a heart rate parameter used for this improvement function evaluation. The implemented safety improvement

function is integrated with other safe computation functions and programmed into device-O, and the computed results are sent out to a display. The desired cardiac health check parameters tachycardia, bradycardia, and arrhythmia/abnormal heart rate are configured in the system and provide prognostic inferences as cardiac healthy or not healthy as output. A serial interface with device-O based on Field Programmable gate Array (FPGA), via an external GUI tool, provides the desired signal tap outputs from the internally implemented safe function for further analysis performed in the MATLAB implemented functions.

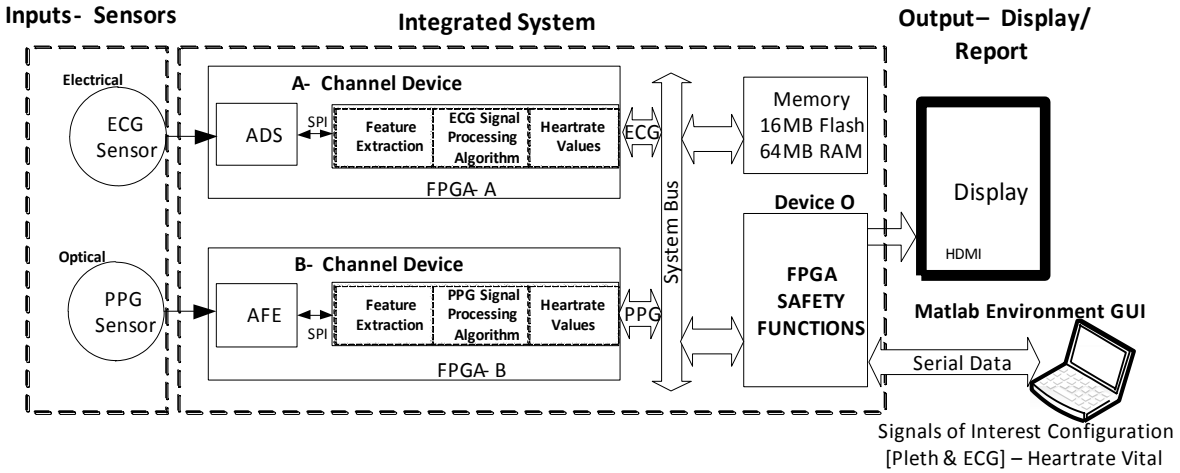


Figure 26:2oo2 (two-out-of-two) Safety-related Cardiac Health Monitoring System Block Diagram.

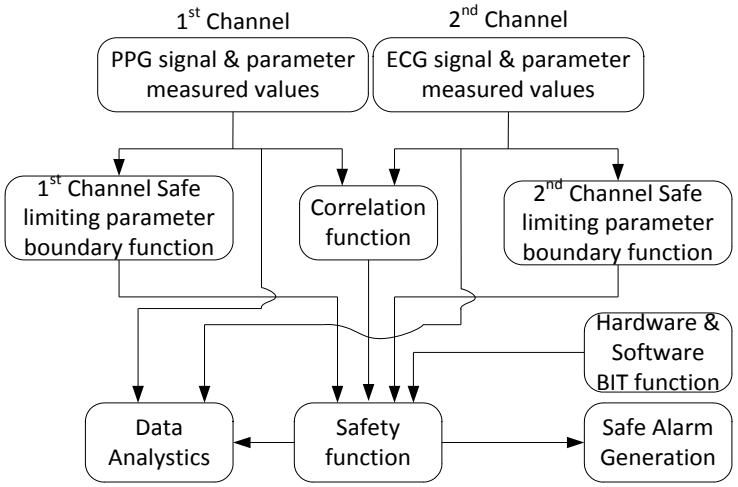


Figure 27: Safety function implementation flow for Accurate Identification and Separation of Signals with and without Faults.

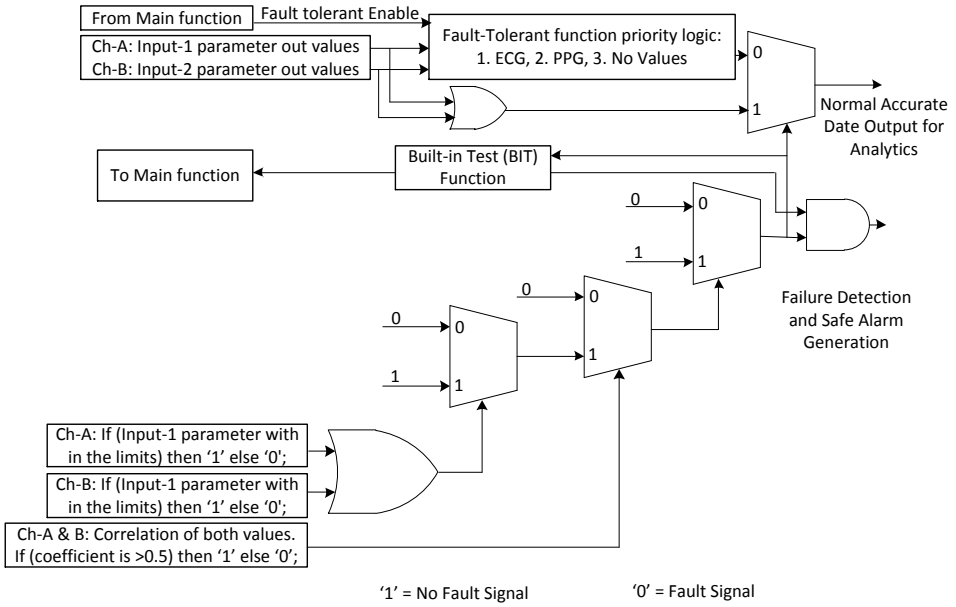


Figure 28: AND-OR Safety function implementation Logic.

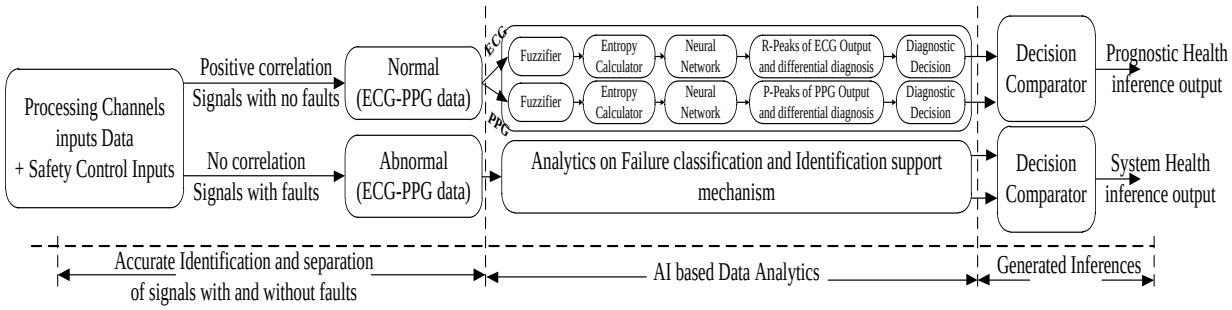


Figure 29: AI-based Data Analytics function flow on Normal and Abnormal for Prognostic health diagnosis.

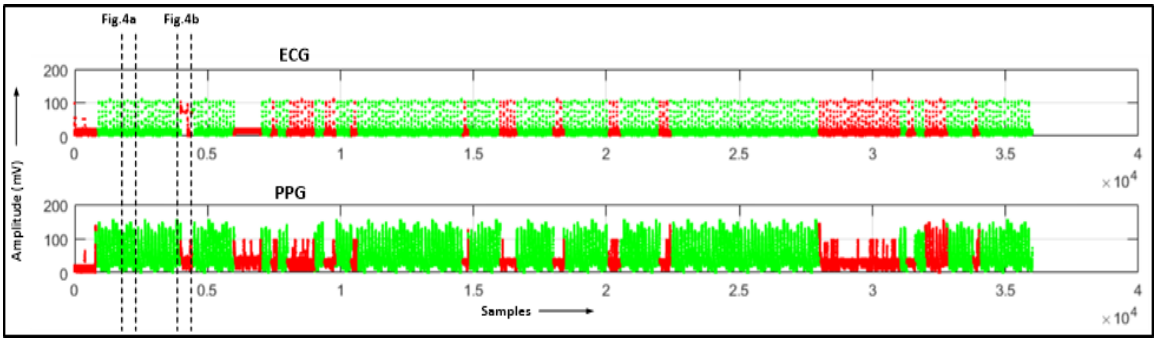


Figure 30: ECG, PPG processed signals captured along with normal (no fault signals highlighted in Green) and abnormal (with fault signals highlighted in Red).

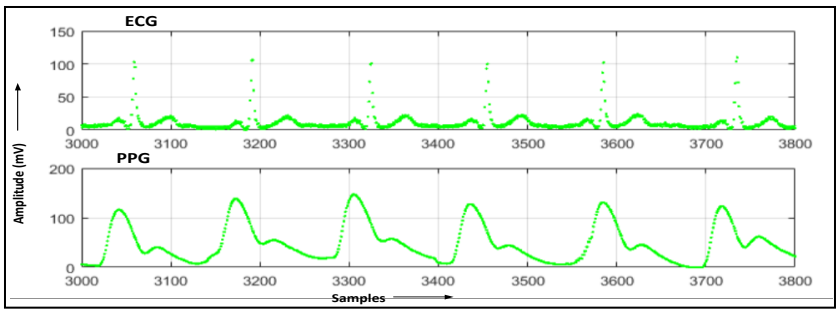


Figure 31: ECG, PPG processed normal signals zoom-in capture.

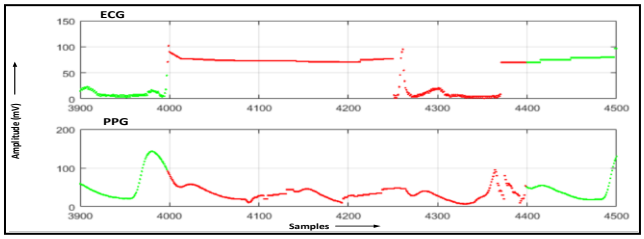


Figure 32: ECG, PPG processed abnormal signals zoom-in capture.

4.4.2 Implementation of Safety improvement Function

The 2oo2 configured safety system consists of two independent channels with each PPG and ECG interface. In addition, the heart rate measured values conditionally correlated using Karl Pearson correlation coefficients with $r_{AB}>0.5$, along with a pre-configured safe boundary limiting comparator parameter function, is detailed [200]. As shown in Figure 27, the outputs from these functions are sent to the safety decision function and the BIT function from hardware and other software functions.

The implemented safety decision function is an AND-OR logic function, as shown in Figure 28, which generates a specific alarm for every detected fault. In addition, this fault signal output determines whether the signal is accurate (as normal with no-fault) or inaccurate (as abnormal with some fault) and sent for further data analytics function implemented based on AI-fuzzy entropy shown in Figure 29.

4.4.3 Application Protocol for Data Acquisition and Analysis

The CHMS was designed as a wearable system, and an application protocol detailed in [200] was followed to gather data from 5- subjects with various age groups conforming to the declaration

of Helsinki. The subjects aged between 15 to 55 years were available for measurement and testing after obtaining informed consent, of which fifty healthy patient data were used.

The system is configured to a 2oo2 safety-related computing platform with desired settings to tap the vital PPG, ECG samples, and post-processed data to record for one hour. A detailed analysis was performed on the collected data in an external interface computing laptop device using a developed MATLAB-based GUI tool called CHMS GUI for test evaluations.

The captured data consists of the pulse counts of post-processing signal (PPG, ECG) data, fault signal data, and data related to normal and abnormal segregated data. The segregated data was graphically presented for visual inspection, and the recorded peak events were tabulated for performance assessments. However, further experiments need to be carried out by configuring the system with a selective combination of sensors like PPG-PPG, ECG-ECG, and PCG-PCG or with cross combinations to assess the performance based on the targeted applications.

4.5 Results and Analysis

The safety function processed data and vital signals captured for one hour from channels ECG, PPG, and outputs presented in Figure 30, Figure 31, and Figure 32 for a single subject. Currently, for preliminary validation of this conceptualized improvement function of accurate segregation of normal and abnormal cardiac vital signals, we considered capturing the signals for one hour each on fifty varied subjects and assessed them. However, to validate the improvement function at the system level, more tests must be performed with a varied combination of sensors to evaluate the functional performance better. The processed data of a single subject and its performance values of the system function tabulated with measured pulses, Se, PPV is in Table 8 and observed signal drift issue during capture, and appropriate sync mechanism needs to improve between the signals and channels. Due to the diverse mediums of sensors utilized and their capturing and processing periods, this system's drift of +/- 2 pulses was identified as a limitation. Detailed analysis of normal segregation-type signals confirms that the count of correct pulses in both channels is almost the same during long-term signal capture with negligible or no incorrect pulses and un-detected pulses recorded.

In contrast, drift issues noticed during short-term signal capture can be mitigated in the design by improving the synchronization mechanism for capturing the signals between the channels. Further investigation of the abnormal segregated type signals helps understand the

causes of various faults within the sensor system, and the related abnormal data is captured in Table 8. However, analysis of this related fault data is out of the scope of this chapter as it requires the definition of failure classification and identification of support mechanisms within the system.

As analyzed, the reading from all fifty subjects is almost similar. The presented results, which show the segregated normal and abnormal signals, provide the correct data for prognostic health diagnostics functions to determine the health parameters. In this AI data analytics, we computed the heart rate vital parameter, which is more accurate. We made conclusions about the subject's health, such as bradycardia (a resting heart rate of fewer than 60 beats per minute is considered bradycardia in adults) and tachycardia (a resting heart rate of more than 100 beats per minute is considered tachycardia in adults). In this chapter, as we focused on the segregation of actual signal data by evaluating the safety function, we used only minimal conditions to infer the subject's health.

Table 8: Performance Analysis of pulse counts at Normal and Abnormal

Segregation Type	***Sensor channel***	***Correct pulses***	***In-Correct Pulses***	***Un-Detected Pulses***	***Se (%)***	***PPV (%)***
Normal	ECG	3979	0	1	99.97%	100%
	PPG	3977	0	2	99.95%	100%
Abnormal	ECG	102	82	14	Faulty signals with "single point of failures."	
	PPG	86	54	38		

Figure 30 shows the capture of PPG and ECG signal data embedded with fault signals for visual inspection. The simultaneous zoom-in captures of the PPG and ECG signals at no fault are shown in Figure 31, with fault shown in Figure 32. i.e., The signals highlighted in green are highly accurate normal signals with no faults and will be further explored with data analytics. The signals highlighted in red are the signals with faults or failures; these signals are further

explored with appropriate data analytics to determine systemic failures or random failures of the system's health, along with the patient's health.

Table 9: 2oo2 Configured CHMS Operational Availability and MTBF Results

Configuration Type	Sensor channel	Up-time [Avg. min] ['t' - 60 min]	Down-time [Avg. min] ['t' - 60 min]	Number of Failures	System Availability	System Availability [Avg of 200 Hrs]	MTBF [~ min]	MTTF [~ min]
1oo1	ECG	48.2	11.8	11	80.33%	84.00%	3.31	3.31
1oo1	PPG	49.6	10.4	6	82.67%	83.00%	6.53	6.53
2oo2	[ECG - PPG]	58.4	1.6	2	97.33%	98.9%	28.40	Not Applicable

Furthermore, the CHMS is evaluated for reliability by measuring the systems Availability, MTBF, Repeatability, and Reproducibility parameters. Table 9 shows the result of higher MTBF value of 28.40 shows improvement in availability from the 1oo1 system. Experimental system evaluation is performed for repeatability and reproducibility following the application protocol. Table 10 shows the measured values have less variance when compared to the 1oo1. However, there are limitations on synchronization delays between channels, which are evaluated and considered to be negligible.

Table 10: 2oo2 Configured CHMS Repeatability and Reproducibility Results

Configuration Type	Sensor channel	Repeatability of CHMS (SD)	Repeatability of CHMS (SDM)	Reproducibility of CHMS
1oo1	ECG	2.16	0.68	0.07
1oo1	PPG	1.52	0.48	1.63
2oo2	[ECG - PPG]	1.20	0.38	0.1414

4.6 Conclusion

In this chapter, the implementation of a safety improvement function in the medical system, which segregates the signals for normal with no fault and abnormal with fault, is detailed. Further, the measured MTBF results for CHMS show improvement in reliability in 2oo2 configuration and less variance in results of repeatability and reproducibility. Furthermore, processing of accurate normal with no-fault signals is computed with a fuzzy entropy-based technique to estimate the apt pulse rate of the subject. Thus, implementing this safe segregation function feature has effectively identified the peaks, detected the apt artifacts, and determined the subject's pulse rate. The right combination of accurate samples from PPG, ECG, and PCG is

necessary, along with AI-based data analytics, to correctly identify artifacts. Improving this selection criterion of sensors combined with the desired diagnostic artifact would enhance the performance of the prognostic analytics of the system. The presented safety approach could be extended for diagnosing cardiac diseases related to the pulse rate information of the subject. Diseases like tachycardia, bradycardia, and arrhythmias can be diagnosed in advance from a set of selected combinations of sensor data along with safety function enhancement in prognostic health diagnostics for accurate interpretations of cardiac abnormalities for better nursing.

Chapter 5. Authentic Measure of Vital Signs Using Fault-tolerant Design Approach with Safety Analytics using 2oo2 Architecture

5.1 Introduction

Advanced smart medical systems engineering for safety-critical medical applications requires considering several dependable features, such as the system's functional safety, availability, and reliability in signal processing algorithms [14][200]. Advancements in high-performance electronics and sensors have become affordable and, thus, increased the usage of these smart medical systems in clinical environments, such as performing critical patient treatments like robotic surgeries and medication supervisory by continuous monitoring of the patients [137][209], [210][211]. These smart, intelligent multimodal computational electronics, along with system portability, come with a significant increase in system complexity and bring in major challenges like functional safety, reliability of measurements, and patient safety. This type of safety-critical smart medical device is often subject to insignificant failures with potentially catastrophic impacts on patients. A study [113][212] of medical device recalls between 2006 and 2011 shows a 69.8% increase in product recalls and a 103.3% increase in the number of adverse events to patients like incorrect medications and lead to deaths, where the majority of the recalls due to the cause of software faults. In a recent report [117], [118] for 2018, a significant spike of 126% increase in product recalls informed the Food and Drug Administration (FDA) of the U.S. where most of the causes are due to software faults. These detected spurious faults interrupt the system functionality and may generate safe alarms during critical periods. However, the cause of numerous spurious alarms, incorrect measurements of vital signs, single points of failure, and undetected faults may have dangerous effects on the patient's nursing. In the recent past, some medical system designs were adopted with safety features and improvements like data fusion and voting techniques [133][134][190][213][214][215]. However, all of these techniques will have their limits and will not be able to solve the issues. For example, they cannot reduce false alarms without finding the real issues, improve fault tolerance by building in safe degradable mechanisms, and give accurate measurements of vital signs without halting the system's operation.

In this chapter, we focused on presenting a safety-related fault-tolerant design approach to improve the safety features in addressing the challenges related to detecting software faults in a non-invasive medical device. The safety features include: 1. Effective fault detection function, 2. Fault-tolerability with safe degradable function. These two functions were implemented and evaluated using the proposed conceptualized 2oo2(2-out-of-2) safety-related design architecture. This approach provides the uninterruptable operability of the system by removing the faults. A detailed framework proposed with five configurable conceptualized safety design architectures based on composite fail-safety techniques realized and evaluated. In addition, a safe degradable function was implemented using Karl Pearson's coefficient of correlation method. Thus, the results are analyzed and evaluated towards reducing alarms for better nursing with reduced alarm fatigue and providing improved authentic vital signs measured values for better predictability of the illness and proper assessment of the patient's condition.

Systematic design assurance guidelines [135][180][216] were followed in the implementation of the proposed architectures. Detailed experimental research activity is performed to evaluate and analyze the results in detail for safety improvements. The conceptual safety-related 2oo2 (2-out-of-2) design architecture has been reused from the previous studies [200] in implementing this proposed conceptual fault-tolerant safety architecture for system functional safety evaluation. Using the proposed design approach, this chapter evaluated vital cardiac signs, like heart rate (HR). The assessment includes the continuity of the measurement of heart rate values and the authenticity of the measured values. Two diverse sensors are selected to detect biomedical signals, and these signals are based on the physical medium of light and electric potential. These sensors, which consist of light-emitting diodes (LEDs) and an optical detector, are used to detect the photo-plethysmogram biomedical signal. An electric-potential integrated circuit (EPIC) sensor is used to detect the electrocardiogram biomedical signal — using two diverse independent algorithms to measure the heart rate in two independent channels in a 2oo2 (2-out-of-2) safety-related design architecture. Analytics were performed on the captured data to detect and identify the potential systemic faults during the vital sign parameter measurement at each independent channel.

A set of measured parametric data, like HR, is collected from two independent channels and correlated to check for any computational faults. Karl Pearson's coefficient of correlation method is used [200] for safe voting logic and to detect the two independent channels'

computational faults. A built-in test fault-tolerant safe degradation function was implemented to identify and isolate systemic and computational faults. Sequence operations are performed for any fault detected, like 1. The System operates in safe mode with safe degradation switching from 2oo2 to 1oo2 or 1oo1 and vice versa towards isolation of the fault and provides authentic data, 2. The System uses negation error codes for each fault category, generates the related alarm for each significant detected fault, and logs the results. Similarly, the experiment is repeated on the proposed conceptualized five design configurations and evaluated for system resilience. The proposed design configurations are:

1. Using diverse ECG and PPG sensors and algorithms at each independent channel to measure the HR.

2. Using different ECG sensors at each independent channel with diverse algorithms to measure the HR.

3. Using different PPG sensors at each independent channel with diverse algorithms to measure the HR.

4. Using a single ECG sensor and measuring the HR with diverse algorithms at each independent channel,

5. Using a single PPG sensor and measuring the HR with diverse algorithms at each independent channel.

For each implemented conceptual architecture, a detailed analysis was done. So, Bland–Altman and correlative plots [217, 218] are used to analyze and show the accuracy of the heart rate measurements and the correlation between two channels of heart rate measurements. In addition, the recorded data, failure detected signal & vital sign heart rate measurements at each channel output, and the safe function output results are analyzed for the effective functioning of fault isolation and reduced a single point of failure (SPOF).

The contributions of this research analysis on this configured medical system prototype with the analytics on data collected by using the safety-related design approaches having interfaces with diverse PPG & ECG sensors signifies,

1. Improvements in eliminating PPG and ECG sensor-related problems in bio-signal detection and identifying the root causes for removing the deficiencies in signal processing techniques to extract authentic vital sign signal information.

2. Efficient predictability in the estimation of illness using accurate data, which eventually improves proper nursing,

3. Improved system operability with less insignificant alarms, enhancing the fault detection method, fault identification mechanism, fault tolerance of the system, and safety integrity level for use in safety-critical applications.

Section 5.2 provides details about the framework to address the specified challenges in the software faults. This framework includes detailed requirements about the conceptualized architectures and their approaches toward the analysis of the challenges. Section 5.3 provides a methodology in detail about the system overview and its realization of two independent channels for experimental studies. Section 5.4 provides the experimental results and analysis of the measured heart rate values, along with the fault alarms between the diverse channels and calculated correlation coefficient values for the safety logic. This section tabulated a Cause and Effect of system analysis, emphasizing authentic measures and safety improvements in the Medical System.

5.2 Theoretical Framework

Work in safety-related electronic systems design and development is multi-dimensional, which means several safety aspects need to be considered in all phases of the product development life-cycle (PDLC) [135][180][216][219]. These related systems should adhere to the standard development processes and guidelines and need compliance to comply with respective standards like IEC, ANSI/AAMI/ CENELEC, RTCA-DO [180][216] the domains like automotive, medical, railways, and aerospace. The aim of any safety-related electronic system should be to detect the fault efficiently. It shall drive the System into a fail-safe mode of system operation based on the severity level of fault that occurs. The systems that cause faults and failures like Random failures, systematic failures, hardware failures, software failures, or any unknown erroneous errors lead to hazardous situations like death, injury, or environmental damage. However, in how effectively we engineer a system for a particular application, a signal processing algorithm plays a critical role in extracting and providing vital information to make decisions. Generally, defining the system requirements for this computation development process always has challenges, dependencies, and limitations with sensors, hardware, and other operational environmental factors. In particular, electronic medical systems, sensors, and related

computational systems provide vital sign information in nursing the subject by monitoring and controlling treatment without any fault or insignificant information. Moreover, the system should not go non-operational during critical surgical procedures in the ICU.

5.2.1 Study of Potential Faults with PPG, ECG Sensor Systems

Recent studies show significant differences in the many brands of patient monitoring systems' bias and precision, even though they use identical hardware. These variances are almost certainly due to the different algorithms used in processing the photo-plethysmogram signal [139][194]. Equally, we used [139] different algorithms in processing the electrocardiogram signal to mitigate the differences in the sensing materials used and the artifact of interest in the signal to be measured. In addition, in-depth studies show that potential faults can be noticed if anything is compromised or missed in defining the system requirements.

In defining the signal processing requirements, considering a few challenging areas [194] in the PPG signal processing, include 1. The selection of LEDs and detectors frequency ranges, 2. Placing the sensor probes at fingertips, ear, nose, or forehead, 3. The non-invasive probing mechanism, either light radiation transmission or reflection, 4. Other considerable effects include changes in saturation, signal quality, effects of dyshemoglobins, dyes, other pigments, and extraneous factors, 5. Physical motion and environmental effects. Equally, in the processing of the ECG signal, the challenging areas [136][139][205][206] include 1. The sensing materials, 2. Noise removal and signal quality 3. Non-invasive probing mechanisms by using with or without dielectric mediums between the probes and subjects, 4. Other considerable effects are subject to physical motion and environmental effects. However, considering these defined requirements and implementation challenges of the signal processing algorithms software, there are limitations and inconsistencies between the algorithms to extract the same vital sign parameter. In the recent past, few experimental studies with varied sample parameter voting and data fusion methods have been used [133][134][138][190][199][215][220][221] for better safety of the device. Furthermore, few studies [133][136][139] reported that the same vital parametric data, like heart rate, can be realized with the different mediums of the sensor.

The present research focuses on the fault-tolerant design approach and a safety aspect in effectively detecting the software computing faults in an algorithmic function using a defined framework and providing accurate measured parameter data with reduced alarms. The presented

framework provides the fault detection and analysis approach and the implementation results using the configurable safety-related 2oo2 design architecture.

5.2.2 Proposed Conceptual Safety Architectures

The proposed 2oo2 (2-out-of-2) evaluated safety-related design approach [200] used for further experimental investigations and performed functional safety assessment to validate the implemented bio-signal processing functions in biomedical systems safety-critical medical applications. The proposed concept evaluates a set of configurable diverse medical sensors and different signal processing algorithms to measure the selected vital parameter. This approach of processing the same parameter in a diverse method, with correlative analytics, offers a scope to improve a useful technique in detecting faults. Furthermore, it provides options to implement fail-safe degradation mechanisms, and related usage of safety-related design architecture provides redundancy and availability.

This chapter considers five concepts for analysis by configuring the System with diverse ECG, PPG sensors, and algorithmic computing software. A correlative analysis has been performed and logs the results for each configuration. It tabulated all analysis inferences for each detected abnormality in the functional software and the results with an analysis of cause and effects towards improving functional safety. The functional description of the 2oo2 architecture includes hardware, software, sensors, and detailed algorithms [200]. The set of five selected configurations for framework analysis is described below.

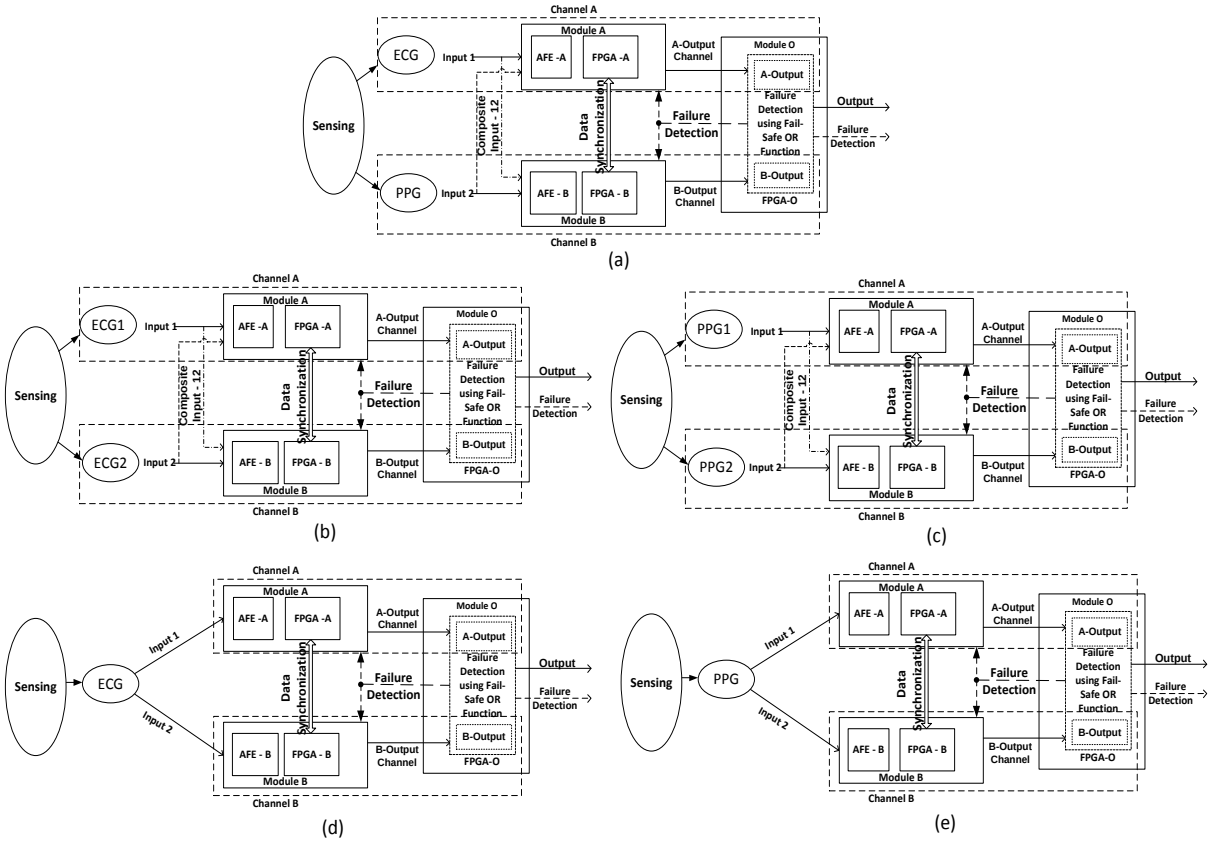


Figure 33: Configurable 2oo2 System (a) ECG, PPG sensor & Diverse algorithm. (b) ECG1, ECG2 sensor & Same algorithm. (c) PPG1, PPG2 sensor & Same algorithm. (d) Single ECG sensor & Same algorithm. (e) Single PPG sensor & Same algorithm.

5.2.2.1 Multimodal Senor configurable 2oo2 System

The 2oo2 System in Figure 33 (a) is configured in 2oo2 with diverse sensor inputs, i.e., the ECG sensor interfaced to Analog Front-end (AFE) device in channel-A and PPG sensor interfaced to the Analog Front-end (AFE) integrated chip (IC) in channel-B. Both channels are configured with selected diverse algorithms [200] to process the heart rate (HR) parameter. Module A and B outputs from each channel correlate with a "safe correlative-bounded configurable limits" function implemented in Module-O to detect the faults and generate the failure detection signal. An output signal consists of accurate parametric data and processed alarm signal data generated by the fault-tolerant safe degradation function. The safe function implementation includes Karl Pearson's coefficient of correlation method, which used [200] a time series sliding window technique between both channels' data and a fault-tolerant safe degradation voting logic function for reliable switching between the channel's computed output.

As part of the framework analysis, we analyzed the recorded output data towards the reliability and efficiency of the implemented algorithmic software function. We provided the inferences on improvements at the systems level requirements. Thus, a practical HR computing function is realized in both channels with authentic HR output with reduced alarms. Similarly, this analysis is further carried out on selected concepts to improve the safety check, such as,

a) A system configured with diverse ECG or PPG sensors with the same algorithms in both channels, as shown in Figure 33 (b) and Figure 33 (c), provides the opportunity to investigate the sensor sensitivity and related deviances in the functional requirement for measuring the same desired parameter.

b) A system configured with one sensor interfacing with both channels, with the same algorithmic function for computation, as shown in Figure 33 (d) and Figure 33 (e), provides the opportunity to investigate the safety function's response to its improvements in defining the requirements. Further, it helps in the evaluation of system-level hardware failure analysis.

5.2.3 Evaluation Framework

Safety compliance is a systematic process used in every step of the product development life cycle. Every safety-related electronic System aims to detect faults when the System is in an active state and shall drive the System into a fail-safe state. The safe state shall be defined based on the mode of system operation in the active state. During the System in operation at a specific mode, the cause of faults and failures is categorized as negation codes. In addition, it needs to be defined by labeling and the severity level of the fault that occurs.

In this chapter, as we focused on a specific signal processing algorithmic software function's functional safety validity, we explained the implemented fault detection logic in the 2oo2 approach, its theoretical fault identification mechanism, and its further evaluation framework.

5.2.3.1 2oo2-Fault Detection Logic and its Analysis

The function 2oo2 fault detection logic receives the parameter input data from channel-A and channel B and is conditionally checked between that particular parameter's threshold limits. The generated outputs are logically ORed as a parallel circuit, and the hardcoded safe output is selected using the correlative coefficient condition (>0.5), which is a moderate to very high state relationship parameter ‘r’ [200], as shown in Figure 34, to generate the fault detection signal.

Further, this fault detection signal is driven back as a feedback input to the primary function, which triggers the diagnostic BIT functions to generate the output enable signal. The primary function triggers a fault-tolerant enable signal for every authentic fault detected. Thus, a predefined priority-based fault-tolerant safe degradation sequence is initiated to select the apt output to pass onto the display. However, if no fault is detected, both channel output parametric values are in a positive relationship. Thus, a selected ORed output and AI-based computed prognostic health inference outputs are released to the display.

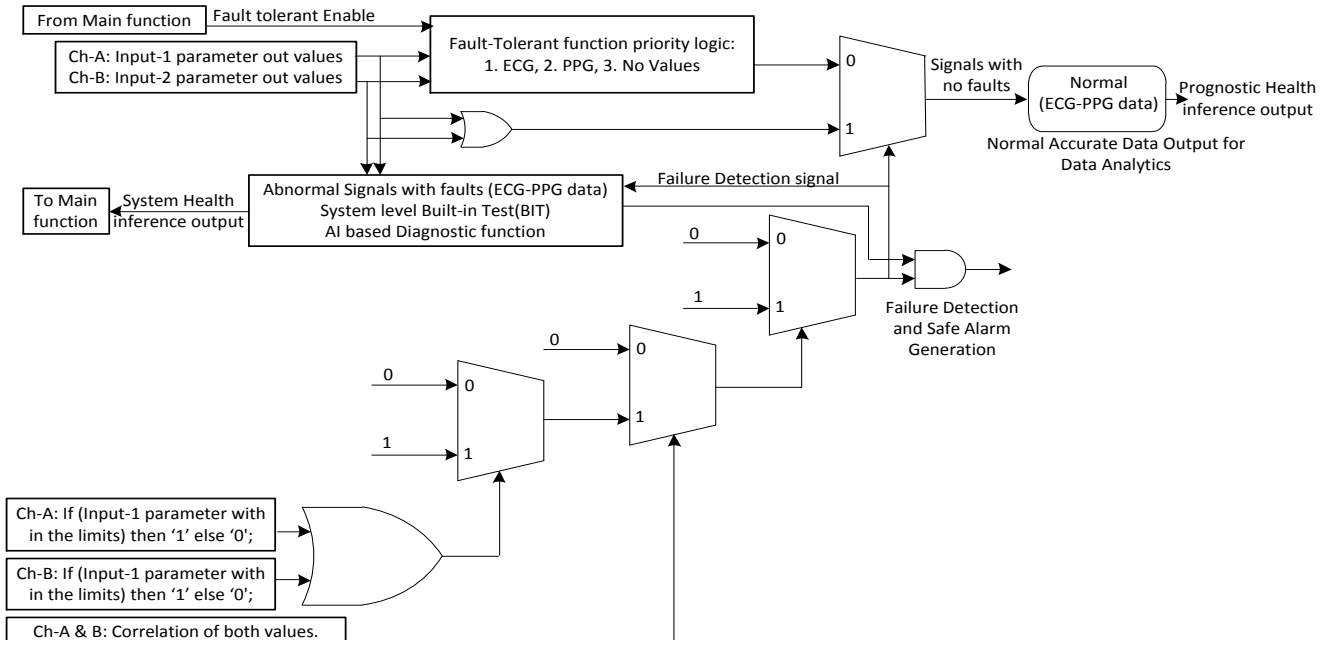


Figure 34: 2oo2 Fault Detection & Fault-tolerant Logic implementation.

In the fault identification mechanism, a defined [200] positive correlation coefficient constant value is compared and continuously monitored to a correlation coefficient value measured between two independently received output-parameter values. Thus, a signal is generated when there is deviance between them. In theory, as per the 2oo2 safety-related voting approach, both channels must fail to initiate the System to fail-safe mode. Thus, a failure detection signal is generated when both the relationship signal and ORed output signal fail. All identified cases are analyzed in Figure 35 from 1 to 8 cases to determine the actual fault. As part of the evaluation framework, all these cases are tabulated in

Table 11 and Table 13 to analyze a selected vital parameter and evaluated by checking the related implemented function's validity for safety.

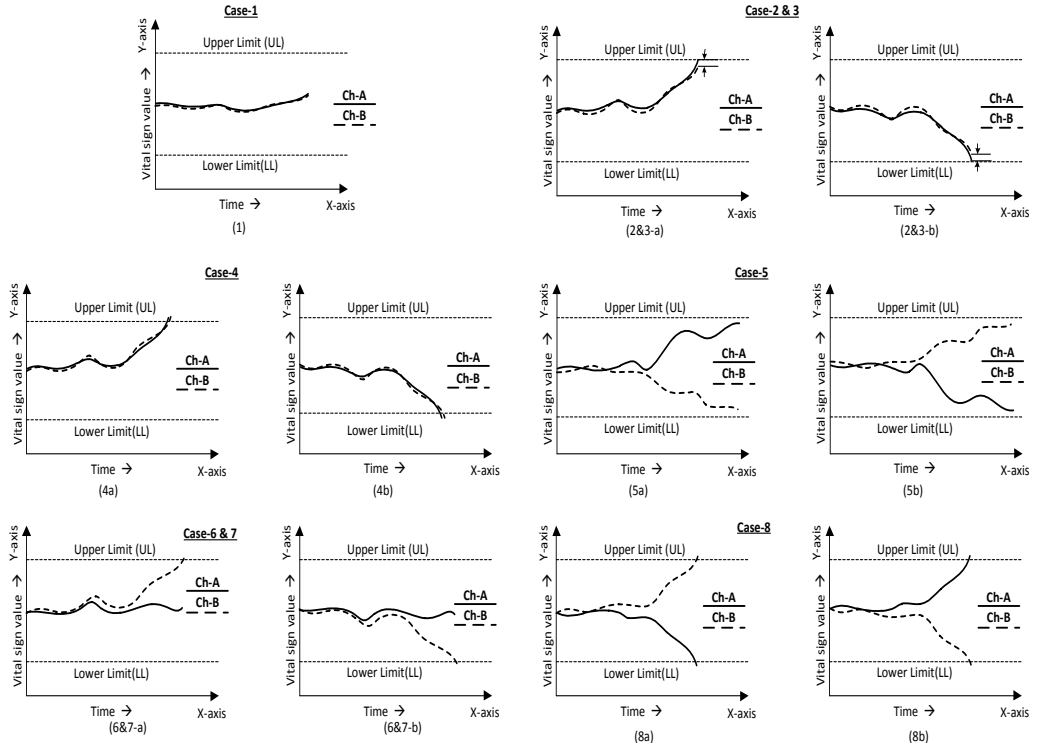


Figure 35: 2oo2 Voting Logic Cases for assessment (1) Values are in a relationship and are in the normal range. (2 & 3)Values in relationship with one signal drifts towards the limit. (4) Values in relationship with both signals drift towards the limit. (5) Values out of a relationship and in the normal range. (6 & 7) Values out of a relationship with one signal drift towards the limit. (8) Values are out of a relationship with both signals drifting towards limits.

Following the standard compliance and best development practices and this design and analysis framework approach in implementing safety-critical medical systems will significantly address the identified challenges and improve the medical system's safety features. A detailed analysis is carried out for a specific vital parameter as part of the evaluation framework. Moreover, preliminary analytical research results show improvements in functional safety by reducing spurious alarms, effectively detecting functional faults, and improving the system's uninterruptable function by providing authentic measurements.

5.3 Methodology

Experimental research activities of this part of the project are divided into three main phases: The first phase is dedicated to the study and evaluation of the aptness to use the safety-related architectures in the targeted non-invasive diagnostic medical monitoring and control systems to measure basic vital parameters and identification of suitable sensors for sensing biomedical

signals like sensing thru electric potential, sound, and light. The second phase is dedicated to designing and realizing three-independent modular designed channels, and each channel is interfaced with a suitable sensor. Each channel module is based on an FPGA design with a modular integrated system interface research prototype built for experimental research studies. The final phase is the validation of the experimental research platform. The system is evaluated with varied configurations with sensors, configurable safety-related architectures, and FPGA circuits. We perform lab and field trials to assess vital parameters like heart rate, address the mentioned challenges, reduce fault alarms, identify algorithm limitations, and improve uninterruptable functionality with safe degradation mechanisms.

The present chapter focuses on the final phase of the research activities to improve the fault detection mechanisms and address the challenges. Using configurable safety-related architectures with a combination of ECG and PPG sensor interfaces, we used [200] the details of the first and second parts of the research prototype build activities and its design evaluation procedures and application protocols.

5.3.1 System Overview

The CHMS is modular and configured to a 2oo2 safety-related computing platform. The System consists of two independent operating channels, shown in

Figure *36* and explained in [200] detail, with CHMS GUI interfaces for test evaluations.

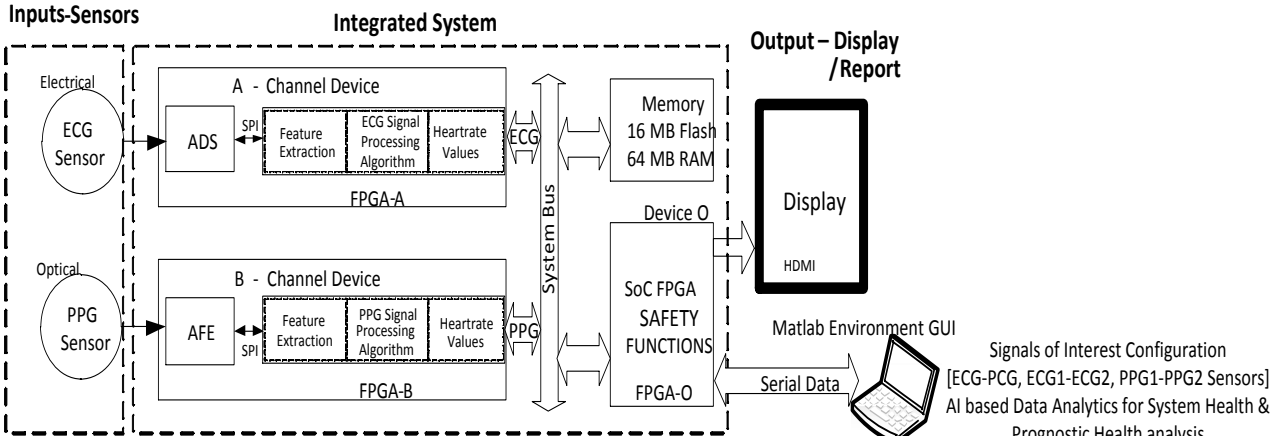


Figure 36: 2oo2 (two-out-of-two) Fault-tolerant Cardiac Health Monitoring System Block Diagram.

5.3.2 Sensors – PPG, ECG and its System configurations

The set of PPG sensors (LEDs and detector), ECG sensors (EPIC and Ag-AgCl electrodes), and the interfaces used in this system configuration are detailed [200]. These combinations of sensors are bonded into a single module for convenience, and each module is placed on a subject at the prescribed location for better measurements. Furthermore, these sensor modules are packaged in modular combinations like ECG-PPG, ECG-ECG, and PPG-PPG. Finally, each module is interfaced with the integrated computing system, as shown in
Figure *36,* configured and evaluated for each conceptual design.

5.3.3 2oo2-based Safe-Voting Method using Correlation Analytics

The prototype system needs to configure 2oo2 with a safe voting mechanism to measure a particular identified vital parametric function. In this system operation approach, channels A and B receive the sample data and compute the vital parameters independently. These measured values are inputs to the safety function, which correlates and votes to generate the alarm output signal and Fault detection signal, as per
Table 11 and Figure 37. Further, the generated signals trigger the related diagnostic functions to process the data to select the authentic vital output for display and the fault alarm signal. Thus, this mechanism of configuring the safe-voting computation shall be performed for each essential parameter measured by the Medical System.

5.3.4 2oo2 Safety-related degradation mechanism

Based on the selected configured parameter in an active system, the System goes into a predefined degradation sequence for any fault detected. These degradation sequences depend on the System's configuration and limitations, such as sensors and availability of the independent processing channels for the same selected parameter. A few identified vital parameters and their feasible degradation scheme are shown in Table 12. Since the System is a modular interface and a provision for high reconfigurability is provided during the System's initial start phase, either to have a high availability system or high safety of the System. Therefore, we can alter the scheme from 2oo2 to 1oo1 for high availability with fault-tolerability (or) 2oo2 to 1oo2 to 1oo1 for high safety with fault-tolerability.

$$Availability = \frac{Uptime}{(Uptime + Downtime)} \qquad (1)$$

Table 11: 2oo2 Based Safe-Voting Logical Truth Table for Fault Detection Using a Correlative Technique.

Evaluation cases	Ch_A	Ch_B	r_{AB}(>0.5) (Correlation coefficient)	Output Signal (2oo2 Fault-tolerant) (O_{AB})	Fault Detection (Diagnostics) Yes/No (F_d)
Case-1	True	True	True	No Alarm	No
Case-2	False	True	True	No Alarm	Yes
Case-3	True	False	True	No Alarm	Yes
Case-4	False	False	True	Alarm	No
Case-5	True	True	False	Alarm	Yes
Case-6	False	True	False	Alarm	Yes
Case-7	True	False	False	Alarm	Yes
Case-8	False	False	False	Alarm	Yes

```
• Do the following in real-time Channel-Ap (ChAp) and
  Channel-Bp (ChBp) measured parameter data.
     For all 'ϵ', ChA ChB
     If (ChAp > LL) ∩ (ChAp < UL) then
      ChA <= True;
     else
      ChA <= False;
     If (ChBp > LL) ∩ (ChBp < UL) then
      ChB <= True;
     else
      ChB <= False;
--Fault Detection (Fd)
     If rAB(>0.5) then
      If (ChA XOR ChB) then
       Fd <= No-Fault;
      else
       Fd <= Fault;
     else
       Fd <= Fault;
--Alarm output Signal (OAB)
     If rAB(>0.5) then
      If (ChA OR ChB) then
       OAB <= True;
      else
       OAB <= False;
     else
       OAB <= False;
```

Figure 37: Pseudocode for Fault detection Analytics and Alarm Output Signal.

5.3.5 Experimental setup and System Evaluation

The experimental setup and application protocol detailed in [200] have been effectively reused to assess the proposed concepts. The MATLAB-based CHMS GUI tool is used to configure and capture the resultant data to Plot.

Table 12: 2oo2 Configured -System Safe Degradation Scheme.

Vital Sign	FAULT-TOLERANT SYSTEM	Degradation Level			System configuration selection scheme for High Availability or Safety Mode	
		1	2	3	High Availability and Fault-tolerant	High Safety and Fault-tolerant
Heart Rate or Pulse	2oo2	1oo2	1oo1	Shut down/Safe mode	2oo2 → 1oo1 →Safe mode	1oo2 →1oo1→ Safe mode
Respiratory Rate	2oo2	1oo2	1oo1	Shut down/Safe mode		
Blood Pressure	2oo2	1oo2	1oo1	Shut down/Safe mode		
Body Temperature	2oo2	1oo2	1oo1	Shut down/Safe mode		
Pulse Oximetry	2oo2	1oo2	1oo1	Shut down/Safe mode		

Table 13: 2oo2 based Cause and Effect - Fault Detection & evaluation Analysis and feasible mitigation solution for the identified cause.

Evaluation cases	Channel-A(ECG) [Parameter within set limits is True else False]	Channel-B(PPG) [Parameter within set limits is True else False]	ECG-PPG r(>0.5) (Correlation coefficient)	Output Signal (2oo2 Fault-tolerant) [True-No Alarm; False-Alarm]	Fault Diagnostics required for Detected Failure Yes/No	Software functional Fault/Negation codes [SW-Software; Ag-Algorithm; F-Function; [4-digit] – Code]	Fault Severity Analysis [No-Fault/Minor/ Major/Critical] (Algorithms function analysis)	Fault description and Probable cause	Mitigation solution for the identified cause
Case-1	True	True	True	True	No	SwAgF4001	No-Fault	Data Authentic	No action
Case-2	False	True	True	True	Yes	SwAgF4002	Minor	▪ Data Authentic ▪ Software Sync/Delay Issue between channels (or) ▪ Negligible higher pulse count detected in ECG	Perform Analytics for consistency (or) Repetitive higher pulse count on ECG signal and rectify the issue.
Case-3	True	False	True	True	Yes	SwAgF4003	Minor	Similarly, as above, for PPG	Similarly, as above, for PPG
Case-4	False	False	True	False	No	SwAgF4004	No-Fault	Data Authentic	No action
Case-5	True	True	False	False	Yes	SwAgF4005	Major	Possible Software Sync/Delay issue between channels	To rectify the issue, perform analytics to check for consistent channel differences.
Case-6	False	True	False	False	Yes	SwAgF4006	Major	Possible cause in Software or Hardware issue	Perform Built-in-Test (BIT) and analytics between channels to rectify the issue.
Case-7	True	False	False	False	Yes	SwAgF4007	Major	Refer above comment	Refer above comment
Case-8	False	False	False	False	Yes	SwAgF4008	Critical	Possible cause in Software or Hardware issue	Perform BIT and Analytics between channels to rectify the issue.

5.4 Experimental Results and Discussion

The System was configured with 1oo1 and captured HR data values Vs. Fault alarm signals individually as ECG-1oo1, PPG-1oo1, ECG2-1oo1, PPG2-1oo1, and presented in Figure *38*(a), Figure *39*(b), Figure *40*(c), Figure *41*(d) from a single subject. The captured alarm data is analyzed to set configurable adjustable upper and lower limits (ADJ-UL & LL) [200].

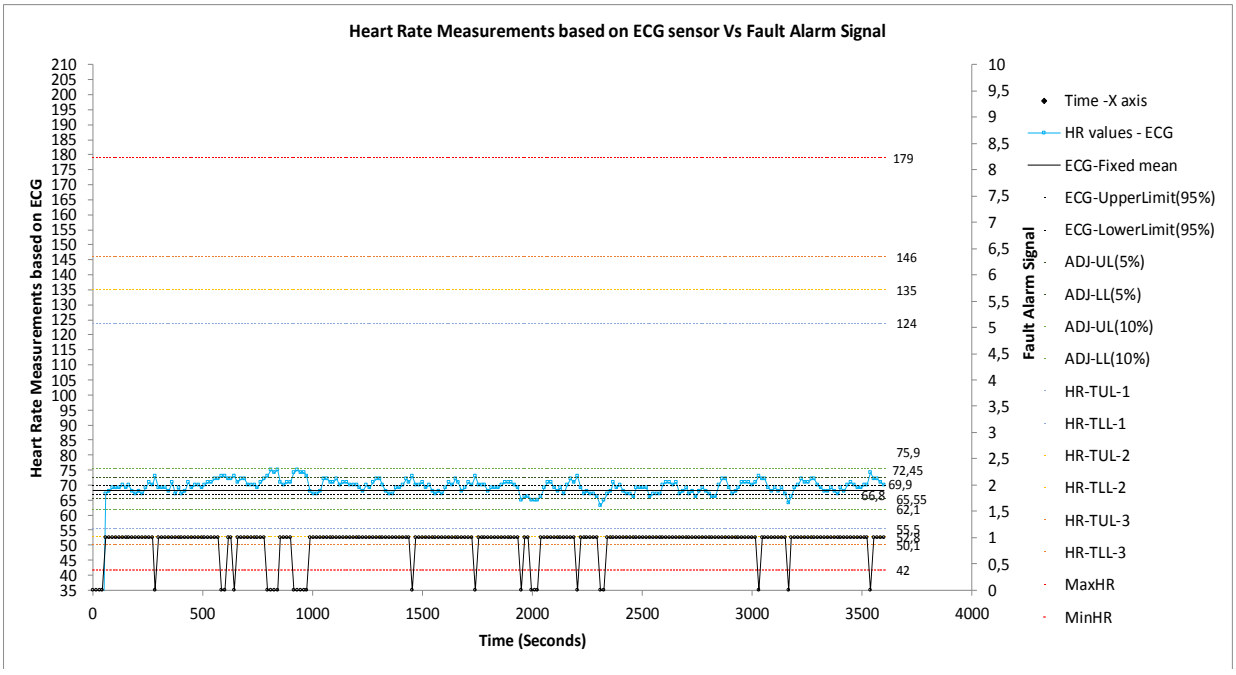


Figure 38: (a) Heart Rate Measurement based on ECG sensor Vs. Fault Alarm signal in 1oo1 configuration.

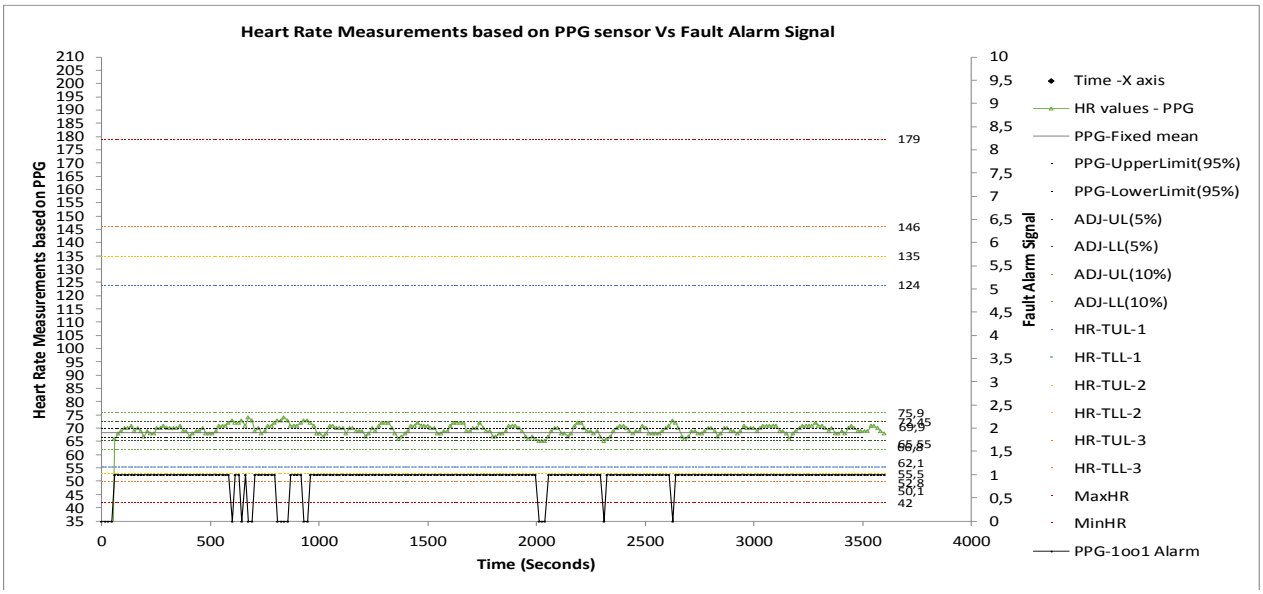


Figure 39: (b) Heart Rate Measurement based on PPG sensor Vs. Fault Alarm signal in 1oo1 configuration.

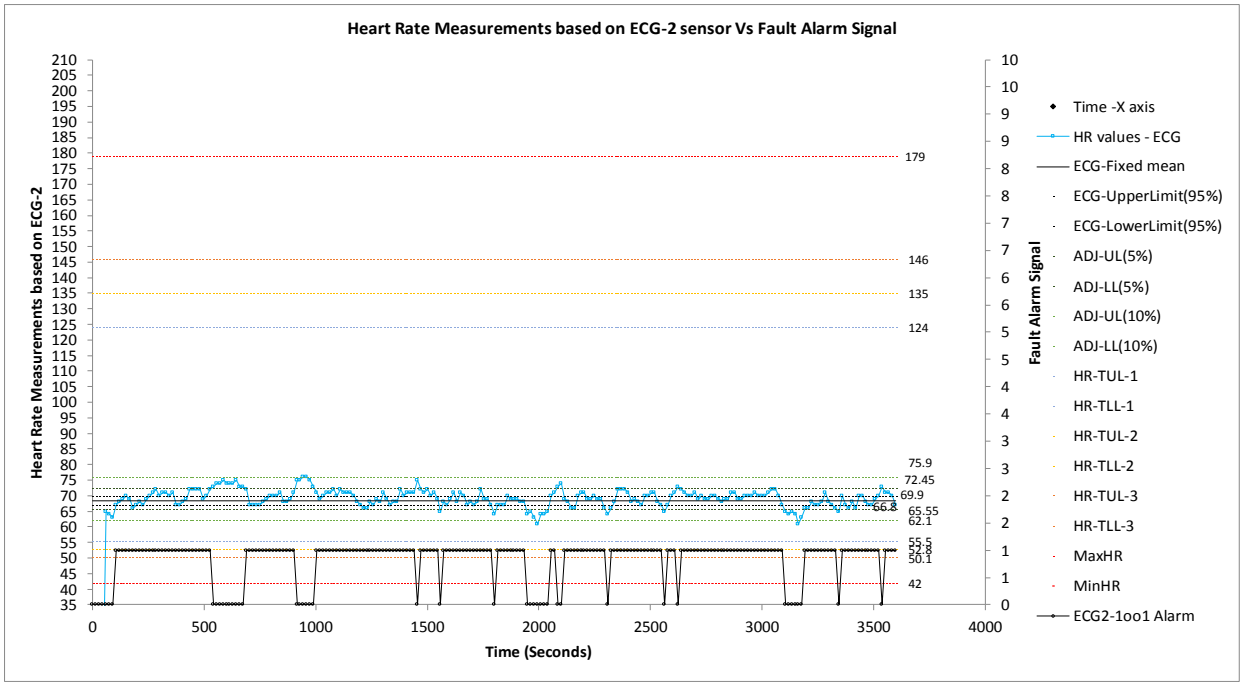


Figure 40: (c) Heart Rate Measurement based on ECG-2 sensor Vs. Fault Alarm signal in 1oo1 configuration.

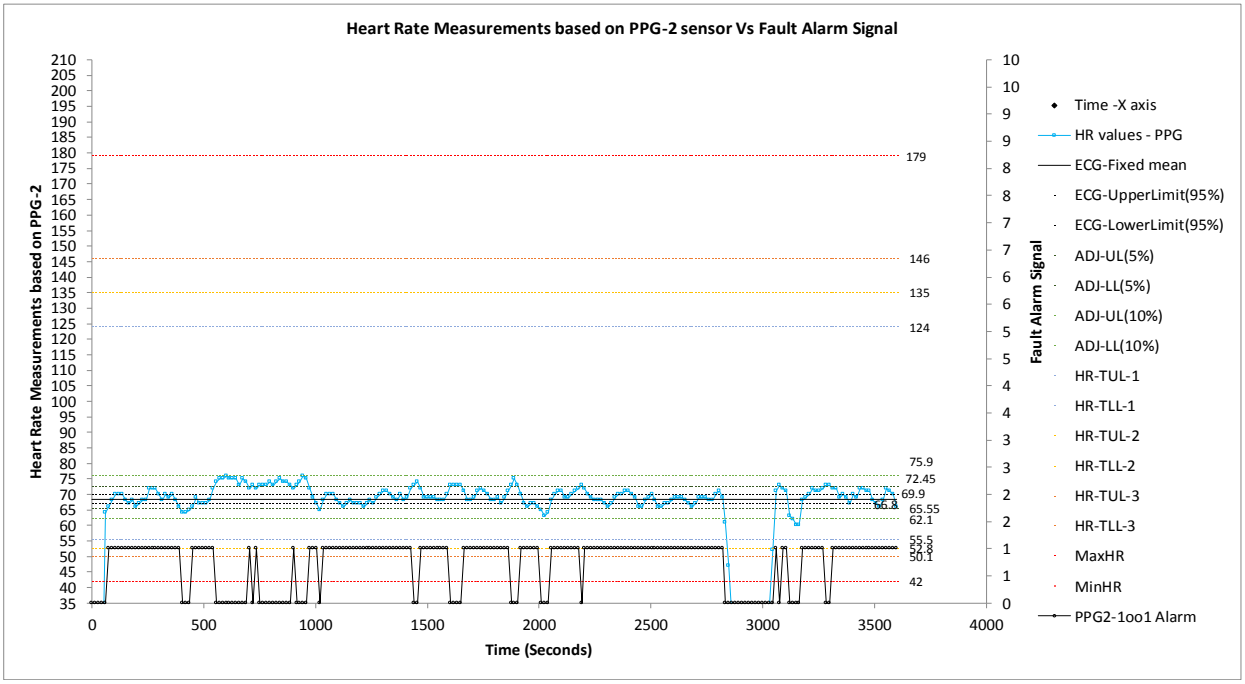


Figure 41: (d) Heart Rate Measurement based on PPG-2 sensor Vs. Fault Alarm signal in 1oo1 configuration.

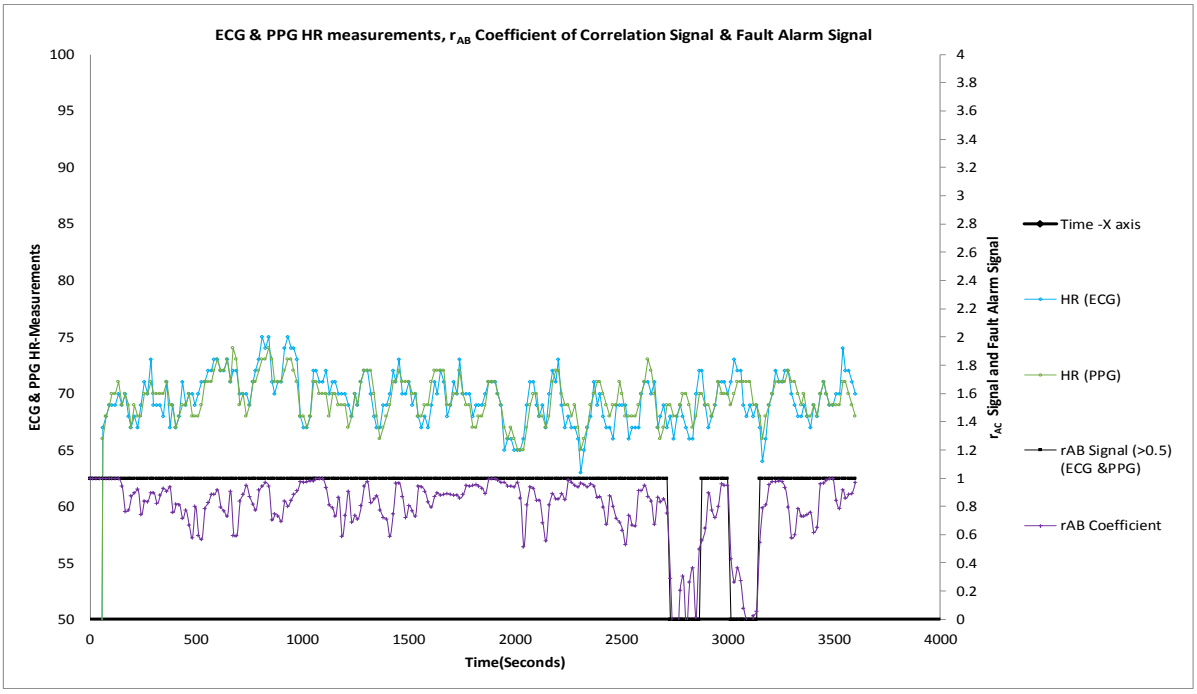


Figure 42: (a) ECG, PPG Heart Rate Measurements, r_{AB} Coefficient of Correlation signal Vs. Fault Alarm signal

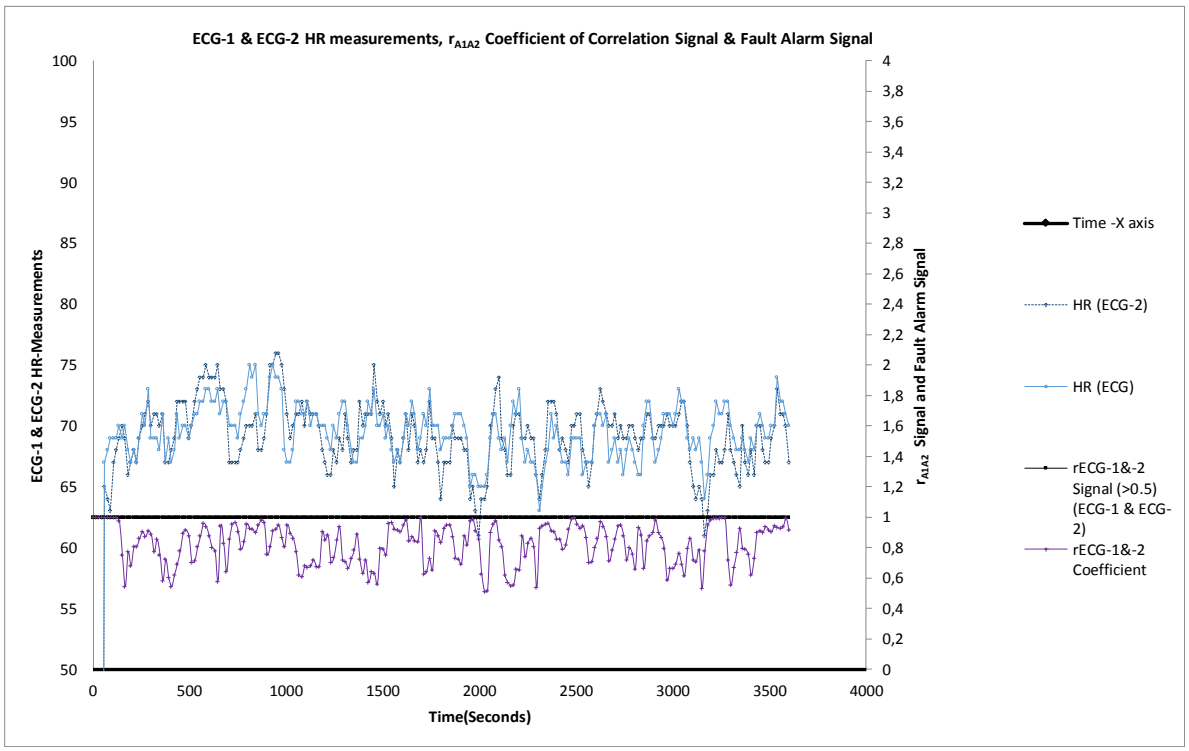


Figure 43: (b) ECG-1, ECG-2 Heart Rate Measurements, rA1A2 Coefficient of Correlation signal Vs. Fault Alarm signal.

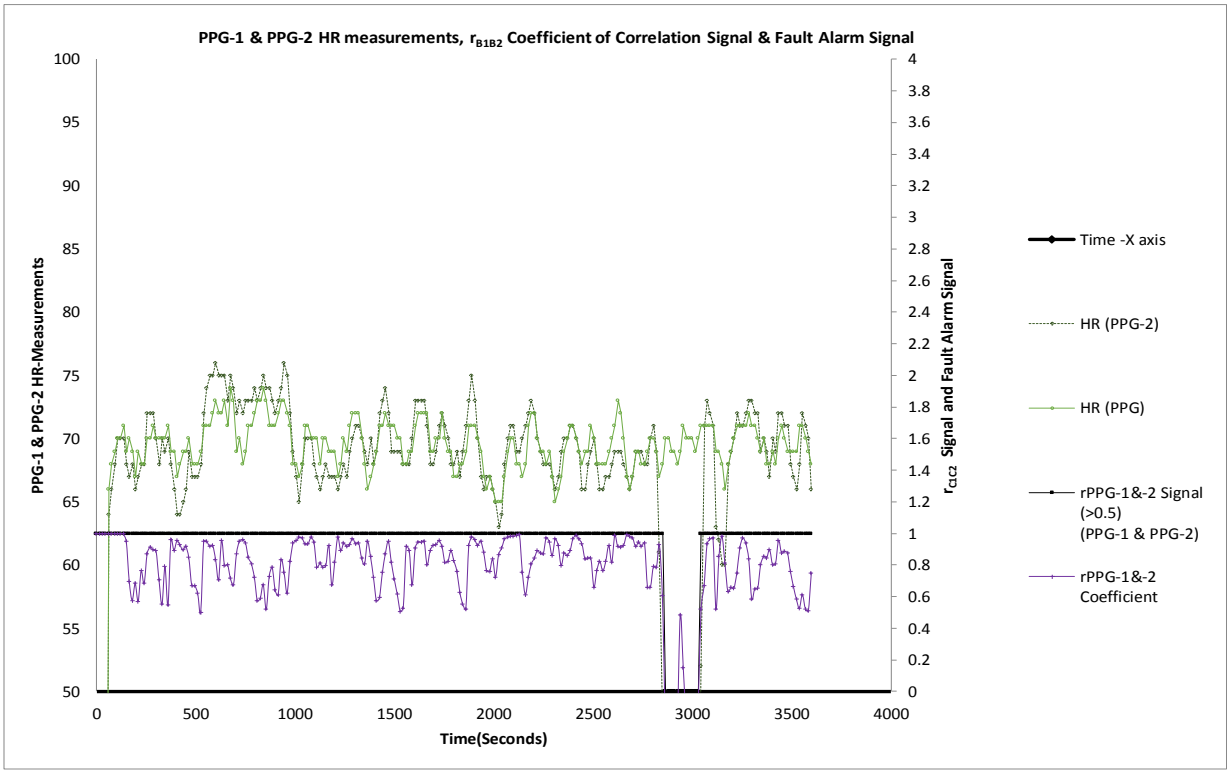


Figure 44: (c) PPG-1, PPG-2 Heart Rate Measurements, r_{B1B2} Coefficient of Correlation signal Vs. Fault Alarm signal.

The configured 2oo2- outputs of ECG-PPG, ECG1-ECG2, PPG1-PPG2 correlation signal Vs. A fault alarm signal is shown in respective Figure 44(a), Figure 44(b), and Figure 44(c). It analyzed that the reduction of alarm readings from all fifty subjects is similar in meeting the objectives. Figure *45*(a), Figure *46*(b), and Figure *47*(c) present the configured 2oo2- results of a single subject, which shows the reduction in alarms and its related cause and effect evaluated analysis presented in Table 13 with inferences.

The sensor's ECG and PPG processed signal data are captured and performed analytics using MATLAB tool by configuring the system in 2oo2 configuration. The tool computes system uptime and downtime by separating the normal and abnormal signal data, as shown in Figure 48. Similarly, the data captured for ECG1-ECG2 and PPG1-PPG2 configurations and results are recorded in Table 14 for a single subject. Following Helsinki's declaration and consent, the monitoring system evaluated fifty subjects of various age groups and recorded the uptime and downtime of the system during evaluation, as an average of 50 Hrs total operating time of the system and calculated system availability in percentile as per equation-1. Table 14 provided

these results along with system health inferences computed per negation codes specified in Table 13 and assessed in these three configurations that the system availability significantly improved from 45 % to 55%.

However, to validate the improvement function at the system level resilience, more tests must be performed with various sensors to evaluate function performance better. It has been observed that during experimentation, limitations exist, such as mainly a signal drift issue during capture, and appropriate sync mechanism needs to improve between the signals and channels. The drift of +/- 2 pulses was a system limitation due to different sensors' mediums, capturing, and measurement periods. Further noticed, the system response time is less than <5 seconds as a limitation. However, a detailed analysis of the uptime period of signals confirms that the count of truthful pulses in both channels is almost the same during long-term signal capture with negligible or no incorrect pulses and un-detected pulses recorded. In contrast, it can mitigate drift issues during short-term signal capture in the design by improving the synchronization mechanism for capturing the signals between the channels.

Further investigation of the uptime and down signals helps understand the causes of various systemic faults within the sensor system. The related fault data is captured, analyzed, and provided for inferences in Table 14. Additional analysis of this corresponding prognostic health data is out of this chapter's scope as it requires defining normal or abnormal vital parameter signal classification and identification of support mechanisms within the system. In this chapter, as we focused on the system availability with reduced alarms by processing the signal data by evaluating the safety function, we used only minimal conditions to infer the system's health.

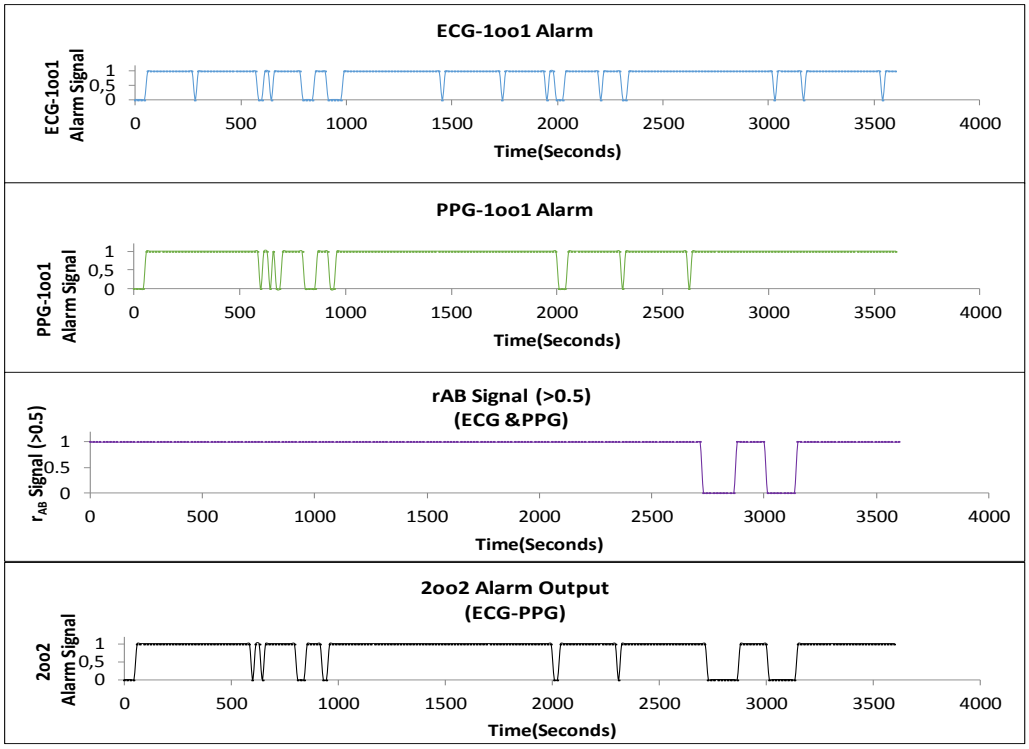


Figure 45: (a) ECG-PPG Recorded 2oo2 Fault Alarm output during Heart rate monitoring in 1-hour period.

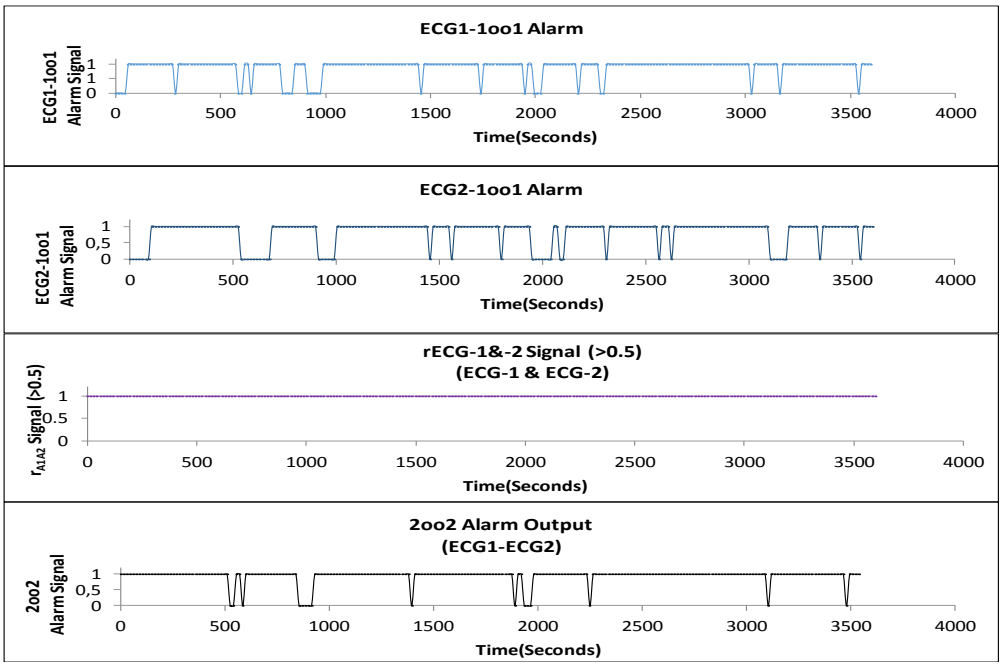


Figure 46: (b) ECG1-ECG2 Recorded 2oo2 Fault Alarm output during Heart rate monitoring in 1-hour period.

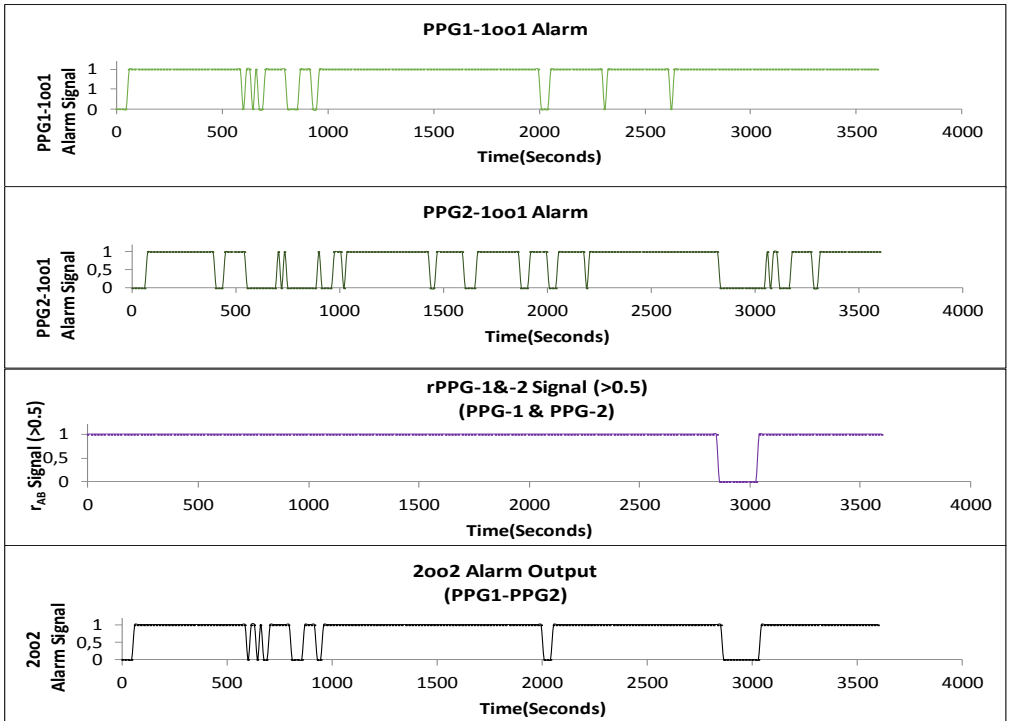


Figure 47: (c) PPG1-PPG2 Recorded 2oo2 Fault Alarm output during Heart rate monitoring in 1-hour.

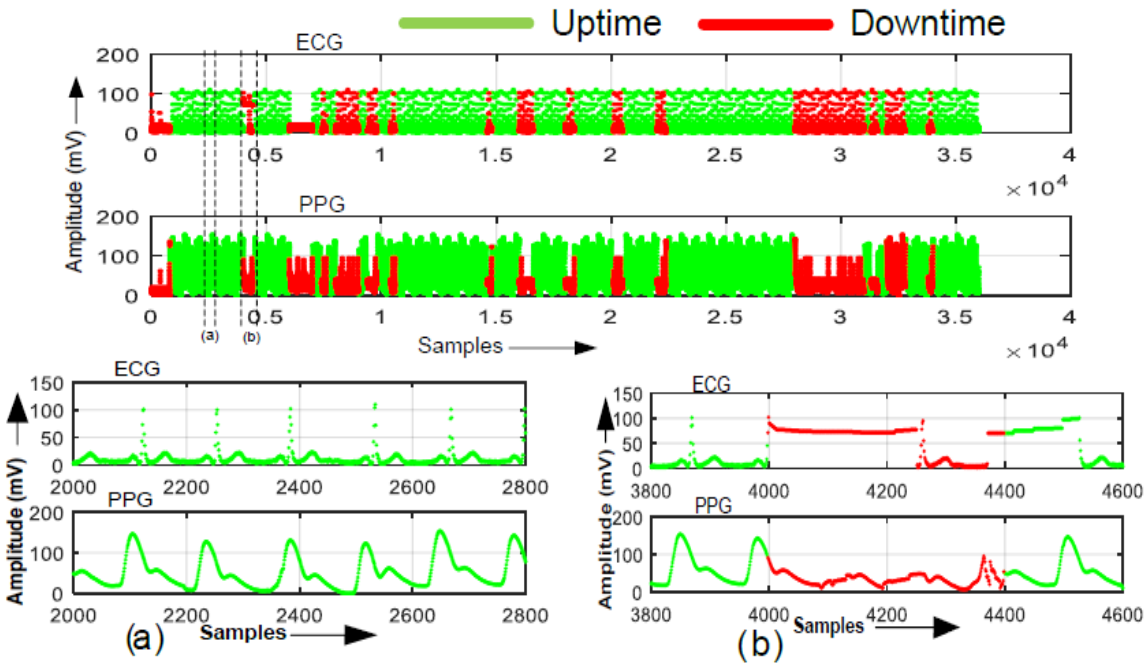


Figure 48: ECG, PPG processed signals data captured using MATLAB tool w.r.t 2oo2 configuration (a) System Uptime – Normal signal data with no-fault (Green). (b) System Downtime – Abnormal signal data with a fault (Red)

Table 14: System Availability Results by Configuring the Fault-tolerant Multimodal Sensor System in 2oo2 System Configuration mode.

Fault-tolerant multimodal sensor System Configuration	Signals	Up-time [Normal Signal] [Avg. minutes] [~'t'- 60 mins]	Downtime [Abnormal Signal] [Avg. minutes] [~'t'- 60 mins]	System Availability configuration	System Availability Average of ~50 Hrs.	Improvement in System Availability using the 2oo2 design approach %Increase	Data Analytics Inferences on System Health – Common Causes
Concept-1 [ECG-PPG] Evaluation of 50 Subjects [1-hour/person]	Channel-A [ECG]	53.4	6.6	89%	90%	57.8%	Main Hardware causes: • ECG/ PCG Sensor probe contact fault. • Power-related faults. Main Software causes: • Data Sync delay Issues between channels due to algorithm computation times • Inaccuracy in detecting the pulses or due to Noise causes.
	Channel-B [PPG]	55.2	4.8	92%	89%		
	Fault-tolerant-Output [ECG-PPG]	58.2	1.8	97%	95%		
Concept-2 [ECG1-ECG2] Evaluation of 50 Subjects [1-hour/person]	Channel-A [ECG1]	54.6	5.4	91%	89%	62.5%	
	Channel-B [ECG2]	56.4	3.6	94%	91%		
	Fault-tolerant-Output [ECG1-ECG2]	58.8	1.2	98%	96%		
Concept-3 [PPG1-PPG2] Evaluation of 50 subjects [1-hour/person]	Channel-A [PPG1]	57.6	2.4	96%	91%	46.4%	
	Channel-B [PPG2]	57.0	3.0	95%	94%		
	Fault-tolerant-Output [PPG1-PPG2]	58.8	1.2	98%	97%		

The presented experimental data was captured from each channel with HR-measured data. In addition, the alarm signal's inverted logic level is logged for the 1-hour duration per subject, considered for evaluating the System. The analysis results show significant improvements in meeting the objectives and a similar systematic approach to further apply this method to other parameter evaluations for safety improvements.

5.5 Conclusion

In this chapter, a concept of fault-tolerant safety-related two-out-of-two design approach implemented and evaluated in the configurable medical cardiac health monitoring system, a research platform, addresses the effective detection of functional faults, improving the uninterruptable function of the targeted medical System by reducing the false or spurious alarms. This framework has significantly reduced the generation of insignificant alarms and increased uninterruptable System availability by 45% to 55%. These findings and the design approach are important contributions to issues related to present medical patient monitoring systems without significant impact on cost since they use the existing system configuration of PPG signal and ECG signals along with FPGA technology devices. While we have focused explicitly on

eliminating identified issues, the conceptual design approach may suit medical monitoring systems, implying that our findings are likely important to designing medical monitoring and control systems. In terms of future research, we suggest using diverse algorithms and sensors (or) evaluation with a combination of these with effective predictive system maintenance, which helps eliminate spurious alarms with reduced downtime of the system and produce more accurate data vital parameters.

Chapter 6. Enhancements in Safety Analytics Using Edge-AI enabled Triple Module Redundancy Design Approach

6.1 Introduction

Technology advancements in multimodal smart sensor systems lead to developments in the sophistication of automated monitoring and alert systems and robotic medical surgery systems[213][214]. However, increased system automation and precision controlling activity during patient nursing bring in more challenges[14][209][226][227][228]. Along with this, the lack of fault-tolerability, uninterruptable system functionality with safe operations, effective fault detections, and identification of authentic signal data for data analytics to perform vital sign measurements adds to the problems. Recently, concerns regarding functional safety due to faults and the effectiveness of uninterrupted continuity of monitoring operations and its related robot-assisted surgeries have heightened the additional safety needs[118][137]. Furthermore, due to the increased number of adverse events associated with monitoring-assisted surgical robots, as reported to the USA Food and Drug Administration (FDA) [113][117][210][229][230], it appears to be essential to address it. This rise is partly due to the exponential upsurge in the number of advanced smart medical monitoring and assistive usage and related robotic procedures over the last decade. In 2012 itself, around 450,000 robotic procedures were performed in hospitals worldwide with an installed base of 2,585 robotic medical systems [215][231][232] and in a recent report [113][233][234][235] in 2019, a significant spike of 126% increase in recalls reported to the U.S. FDA, where the majority of the causes due to software faults in medical patient monitoring assistive technology.

This chapter focuses on an extended experimentation of the 2oo2(2-out-of-2) design approach [236], which emphasizes the fault-tolerant safety-related 2oo3(2-out-of-3) design approach to enhance the safety features in addressing the systematic failure challenges related to detecting functional software faults in a medical monitoring assistive system. The safety features include:

1. Effective systematic fault detection function,
2. Fault-tolerability with safe degradable function.

These two functional features are implemented and evaluated using the proposed 2oo3(2-out-of-3) configurable safety-related design architectures to mitigate the challenges. This

improves the effective detection of functional faults and the uninterrupted system operation, even if the system is affected by a single point of failure (SPOF). A detailed framework is presented with a configurable and conceptualized 2oo3 safety design architecture based on the fail-safe technique, which was realized and evaluated. A safe degradation function is realized using Karl Pearson's coefficient of correlation method. Thus, the results are analyzed and evaluated for effective algorithmic fault detection and safe degradation mechanism for the continuous operability of the system in assisting the feedback controls of automated robotic surgical procedures. This approach reduces system fault alarms for better nursing with reduced alarm fatigue. Also, it provides improved authentic vital signs measured values for better predictability of the illness and proper assessment of the patient's condition by giving feedback to the safety-critical medical systems for effective precision controlling.

The systematic design assurance guidelines [135][180][216] are followed in implementing the proposed safety-related architecture in building the prototype. In addition, detailed experimental research is performed to evaluate the results and further analyze for safety improvements. The conceptual safety-related 2oo3 (2-out-of-3) design architecture or triple module redundancy (TMR) design architecture was used from the previous studies [200] in the implementation of this safe design approach. Furthermore, this chapter introduces the notion of correlation between multiple channels in a 2oo3 system with the objective of minimizing the spurious alarms and chances of failures. This chapter evaluated the cardiac vital sign parameters like heart rate (HR) using the proposed 2oo3 safe design approach. The assessment includes the continuity of the measurement of heart rate values and the aptness of the measured values. A set of three diverse sensors is selected to detect the biomedical signals, and these signals are based on diverse physical media like Light, Sound and Electric potential. In addition, a hybrid sensor, consisting of a set of light-emitting diodes (LEDs) and an optical detector, is used to detect the photoplethysmogram (PPG) signal.

A digital micro-electro-mechanical system (MEMS) sensor detects the phonocardiogram(PCG) signal. An electric-potential integrated circuit (EPIC) sensor detects the electrocardiogram(ECG) signal. Three diverse independent algorithms were used to simultaneously measure the heart rate in three independent channels in a 2oo3 (2-out-of-3) safety-related design architecture. A detailed observation is recorded and evaluated for potential measurement errors and systemic faults during the measurement of the vital sign parameter like

the heart rate (HR) parameter at each independent channel using PPG, PCG, and ECG signals. A set of measured HR parametric data was collected periodically from three independent channels and correlated to check for any computational faults. Karl Pearson's coefficient of correlation method is used for a safe voting function and implemented to detect the computational faults between the three independent channels. A built-in test (BIT) fault-tolerant safe degradation mechanism is implemented to identify and isolate systemic and computational faults. A set of diagnostic sequence operations performed for any fault detected, like 1. The system operates in safe mode with safe degradation switching from 2oo3 to 2oo2, 2oo2 to 1oo2 or 1oo1 and vice versa towards isolation of the fault and provides authentic data, 2. The system uses the predefined negation error codes for each fault category, generates the related alarm for each significant detected fault, and logs the results. A detailed functional analysis is carried out, and the accuracy of the cardiac vital sign heart rate measurements, along with the coefficient of correlation results of vital sign measurements between three channels, are analyzed using Bland–Altman and correlative plots [217][218]. The recorded data consists of a log of failure detected output signal and vital sign heart rate measurements at each channel output along with results of safe, functional, built-in diagnostic outputs analyzed for the effective functioning of fault isolation and reduction of single-point-of-failure (SPOF) using safe degradation function and safe correlation function.

The contributions of this research analysis by this configurable medical system prototype, with data collected, using this optimized TMR approach and having interfaces with diverse PPG, PCG, and ECG sensors, signifies,

1. Drastic improvement in the elimination of PPG, PCG, and ECG-related problems in bio-signal detection and removing the deficiencies in signal processing methods to extract the authentic vital sign signal information,

2. Efficient predictability in the estimation of illness, which eventually improves in monitoring the subject health and proper nursing,

3. Significant improvement in system active time with much fewer unimportant alarms, thus improving the system's fault tolerability and safety integrity level (SIL) for usage in safety-critical medical applications like medical robotics or improving instrument intelligence.

Section 6.2 details the framework in order to address the specified challenges in the detection of software faults. This framework includes requirements about the conceptualized

TMR architecture and the approach to analyzing the challenges. Section 6.3 provides a methodology in detail about the system overview and its realization of three independent channels for experimental studies. Section 6.4 evaluated the experimental results of the measured heart rate values, the fault alarms between the diverse channels, and the correlation coefficient values calculated for the safety logic. Finally, in Section 6.5, a detailed discussion of the results and further application of this approach to other parameters will emphasize authentic measures and safety improvements.

6.2 Theoretical Framework

This part of the research study is an extended experimentation of the 2oo2(2-out-of-2) design approach and re-uses the experimental framework described in section 5.2. This study presents the safety-related 2oo3(2-out-of-3) design approach to evaluate the safety features in addressing the systematic failure challenges related to detecting functional software faults in a medical monitoring assist system.

6.2.1 Investigations of potential faults in a Medical Instrumentation System

Recent investigations show significant differences in the many brands of patient monitoring systems on signal biasing and precision, even though they use similar hardware. These variances are almost certainly due to the different algorithms used in processing the photoplethysmogram signal [136][194], the Phonocardiogram signal[137][237], and the electrocardiogram signal[136]. To reduce the effects of variations in the sensing materials employed and the artifact of interest in the signal to be measured, we used alternative approaches for processing these ECG, PCG, and PPG signals. In-depth studies show potential faults can be noticed if anything is compromised or missed in defining the system requirements. By defining the design requirements and its approach, we considered a few challenging areas from the PPG system example[194][238], including

1. The selection of sensor’s and detector's frequency ranges,
2. Placement of the sensor probes at different locations such as fingertips, ear, nose, and forehead,
3. Mechanisms of non-invasive probing, either light radiation transmission or reflection,

4. Other considerable effects like changes in saturation, signal quality, effects of dyshemoglobins, dyes, other pigments, and extraneous factors,
5. Subject in physical motion and environmental effects.

Equally, in the processing of the ECG, the PCG signal is considered a similar challenging area[136][237]. However, considering these defined requirements and the implementation of the signal processing algorithms software, there may still exist some inconsistency between the algorithms to extract the same vital sign parameter due to faults or limitations at a certain level. Therefore, in the recent decade, a few experimental studies with varied sample parameter voting and data fusion methods have been used [133][134][137][138][190][199] [205][206][219][220] for better device safety.

Moreover, few studies [136][137] reported that the same vital sign parametric data, like heart rate, can be realized with the different mediums of the sensor. The present research chapter focuses on the fault-tolerant safety-related design approach and a safety feature in effectively detecting systematic failures using a defined framework and providing accurate measured parameter data with reduced alarms. Systematic failures such as safety instrumented functional design errors, hardware design errors, and software computing faults in an algorithmic function. The presented framework provides the fault detection and analysis approach and the implementation results using the configurable safety-related 2oo3 design architecture.

6.2.2 Optimized Conceptual Fault-tolerant 2oo3 Design and Analysis Framework

The proposed 2oo3 (2-out-of-3) evaluated safety-related design approach [200] used for further experimental investigations and performed functional safety assessment to validate the implemented bio-signal processing functions in biomedical instrumented systems for safety-critical medical applications. The proposed concept evaluates configurable diverse medical sensors and different signal processing algorithms to measure the selected vital parameter. This approach of processing the same parameter in a diverse method, with correlative analytics, offers a scope to improve a useful technique in detecting faults. Additionally, it provides options to implement fail-safe degradation mechanisms, and related usage of safety-related design architecture provides redundancy and availability.

This chapter considers 2oo3 (2-out-of-3), called the triple modular redundancy (TMR) concept, for analysis by configuring the system with diverse ECG, PCG, and PPG sensors and

diverse algorithmic computing software. A correlative analysis is performed and logs the results for the set configuration. Additionally, it tabulates all prescriptive maintenance inferences using edge-AI-based cause and effect analytics for each detected abnormality in the functional software and the results with analysis of cause and effects towards improving functional safety[239]. The functional description of the 2oo3 architecture includes hardware, software, sensors, and the algorithms used, as detailed in [200]. The selected 2oo3 configuration and its framework analysis are described below.

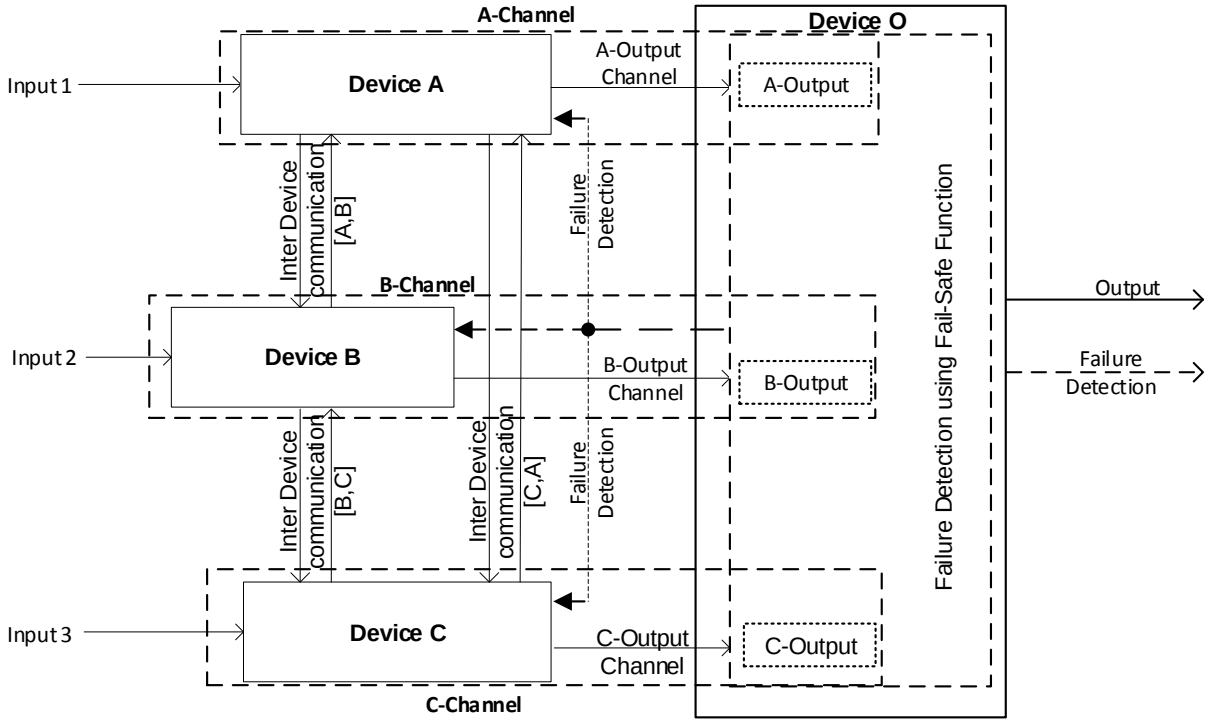


Figure 49: Configurable TMR or 2oo3 safety-related System.

6.2.2.1 Multimodal Senor configurable 2oo3 (2-out-of-3) System

The System in Figure 49 is configured in 2oo3 (2-out-of-3) with diverse sensor inputs, i.e., the ECG sensor interfaced with Analog Front-end (AFE) device in channel-A, a PPG sensor interfaced to the Analog Front-end (AFE) integrated chip (IC) in channel-B and a digital microphone based PCG sensor interfaced with interface circuitry in channel-C. These channels are configured with selected diverse algorithms [200] to process the heart rate (HR) parameter. The outputs of module A, B, and C, from each channel, is correlated with a "safe correlative-bounded configurable limits" function implemented in Module O to detect the faults and generates the failure detection signal. An output signal consists of accurate parametric data and

processed alarm signal data generated by the fault-tolerant safe degradation function. The safe function implementation includes Karl Pearson’s coefficient of correlation method, which used [200] a time series sliding window technique between the channel's data and a fault-tolerant safe degradation voting logic function for reliable switching between the channel's computed output.

As part of the framework analysis, we analyzed the recorded output data towards the reliability and efficiency of the implemented algorithmic software function. We provided AI-based inferences based on defect density for the improvements at the systems level functional requirements. Thus, a practical HR computing function is realized in these channels with authentic HR output with reduced alarms. Similarly, this analysis is further carried out on various segments of the design to improve the safety check, such as,

a) System configured with diverse or same sensors with the same algorithms in both channels, which provides the opportunity to investigate the sensor sensitivity and related deviances in the functional requirement for measuring the same desired parameter.

b) A system configured with one sensor interfacing in all channels, with the same algorithmic function for computation, provides the opportunity to investigate the safety function response to its improvements in defining the requirements. Further, it helps in the evaluation of system-level hardware failure analysis.

6.2.3 Framework Evaluation

Safety compliance is a systematic process in every product development life cycle (PDLC) phase. Every safety-related electronic system aims to detect faults, and while in an active state system, it shall drive the system into a fail-safe state. The safe state shall be defined based on the mode of system operation in the active state. During the System in operation at a specific mode, the cause of faults and failures is categorized as negation codes. In addition, it needs to be defined by labeling and the fault's severity level.

In this chapter, as we focused on a specific signal processing algorithmic software function's functional safety validity, we explained the implemented fault detection logic in the 2oo3 (2-out-of-3) approach, its theoretical fault identification mechanism, and its further evaluation framework.

6.2.3.1 2oo3-Fault Detection Logic and its Analysis

The function 2oo3 (2-out-of-3) fault detection logic receives the parameter input data from channels -A, -B, and -C and conditionally checks between that particular parameter's threshold limits. The generated outputs are logically ORed as a parallel circuit, and the hardcoded safe output is selected using the correlative coefficient condition (>0.5), which is a moderate to very high state relationship parameter ‘r’ [200], as shown in Figure *50*, to generate the fault detection signal. Further, this fault detection signal is driven back as a feedback input to the primary function, which triggers the diagnostic Built-In-Test (BIT) functions to generate the output enable signal. The primary function triggers a fault-tolerant enable signal for every authentic fault detected. Thus, a predefined priority-based fault-tolerant safe degradation sequence is initiated to select the apt output, to pass onto the display. However, if no fault is detected, both channel output parametric values correlate positively. Thus, a selected ORed output is released to the display and AI-based computed prognostic health inference outputs.

In the fault identification mechanism, a defined [200] positive correlation coefficient constant value is compared and continuously monitored to a correlation coefficient value measured between two independently received output-parameter values. Thus a signal is generated when there is a deviation in the relationship between them. In theory, as per the 2oo3 safety-related voting approach, any two channels must fail to initiate the System to fail-safe mode. Thus, a failure detection signal is generated when the relationship signals and ORed output signal fail. All identified cases are analyzed, as detailed in

Figure *51*, from 1 to 8 cases to determine the actual fault. As part of the evaluation framework, all these 64 cases are tabulated in Table *17* to analyze a selected vital parameter and evaluated by checking the related implemented function's validity for safety.

Following the standard compliance and best development practices and this design and analysis framework approach in implementing safety-critical medical systems will significantly address the identified challenges and improve the medical system's safety features. A detailed analysis is carried out for a specific vital parameter as part of the evaluation framework. Moreover, preliminary analytical research results show improvements in functional safety by reducing spurious alarms, effectively detecting functional faults, and improving the system's uninterruptable function by providing authentic measurements.

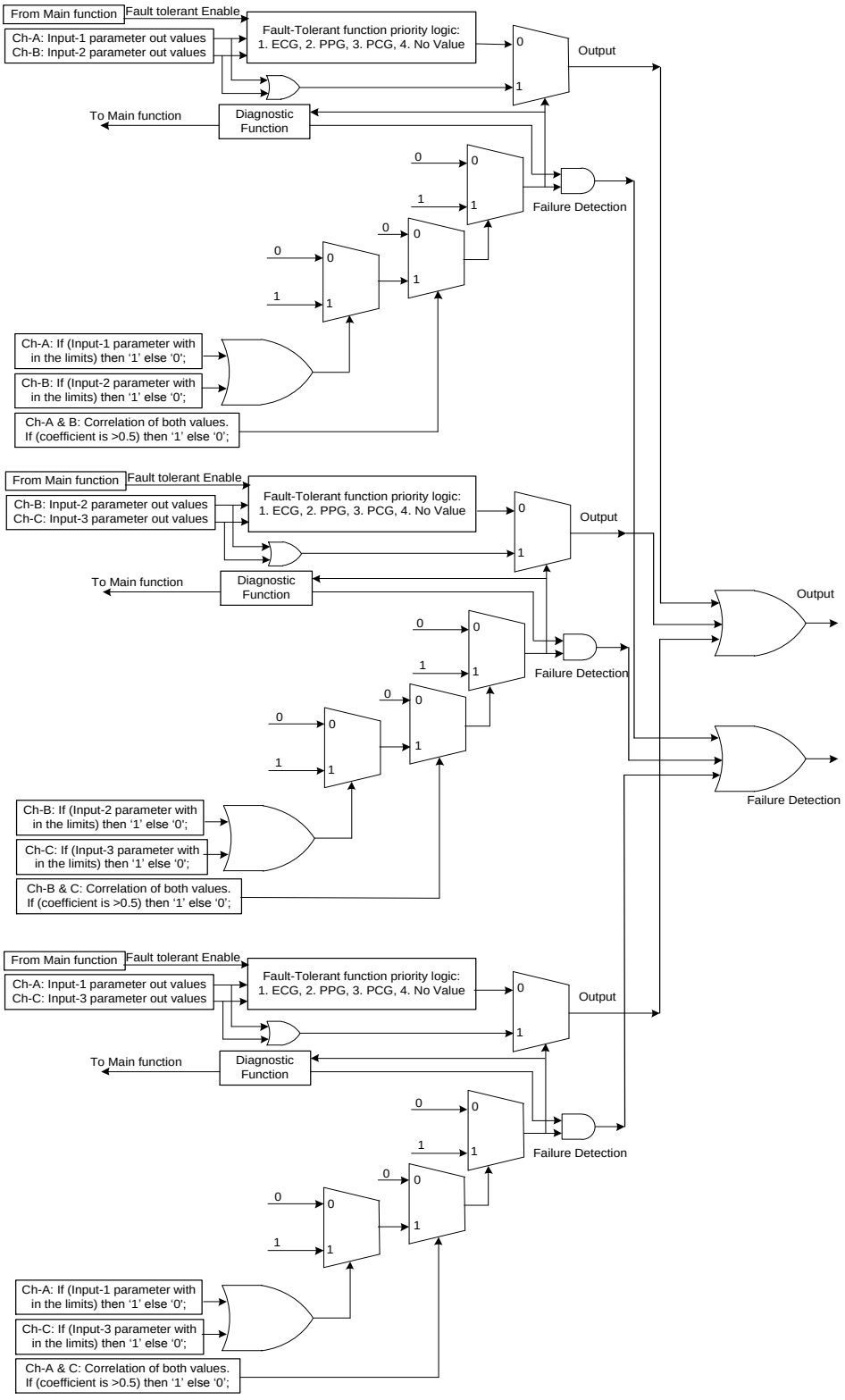


Figure 50: 2oo3 Fault Detection and Fault-tolerant Logic implementation.

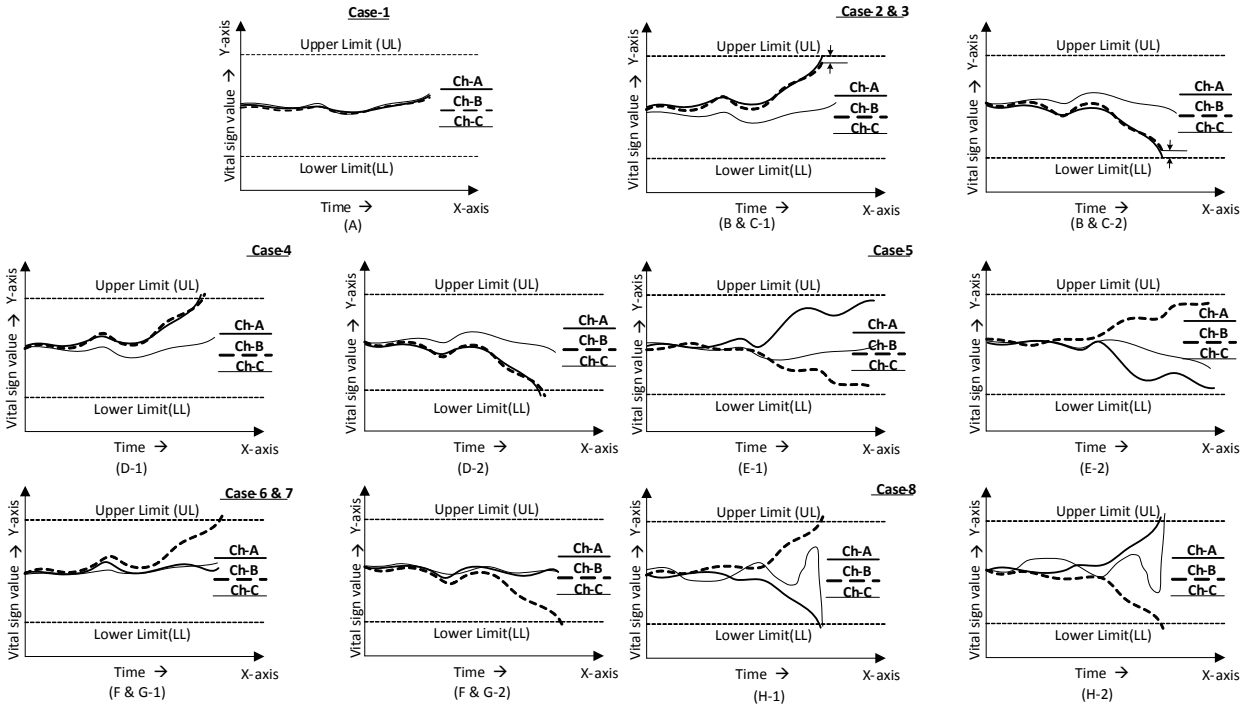


Figure 51: 2oo3 Fault Detection and Fault-tolerant Logic implementation. 2oo3 Voting Logic Cases for assessment (A) All channel values are in a relationship and are in the normal range. (B & C) At least two channel values in relationship with one signal drift towards the limit. (D) At least two channel values in relationship with both signals drift towards the limit. (E) All channel values are out of a relationship and in the normal range. (F & G) Two-channel values out of a relationship with one signal drift towards the limit. (H) All channel values are out of a relationship, and the signals drift toward limits.

6.2.3.2 2oo2 configurations Comparative analysis and Necessity for -2oo3 architecture Evaluation

A detailed analysis is performed on the results of -2oo2 configurations presented in the earlier Chapters 3 and 5 are shown in Table 15. Observed that -2oo2 configurations of ECG-PCG, ECG-PPG show significant improvement in Availability from 45% to 65% when compared with independent channels of ECG, PCG and PPG. However, the selected HR parameter can be measured from these independent channels, and our theoretical analysis shows that in 2oo3 system configuration, the system will further improve in Availability due to an increase in channel redundancy.

Table 15: System Availability Results by Configuring the CHMS in 2oo2 System Configuration

Configuration Mode	Signal Channels	Up-time [Normal Signal] [Avg. minutes] [~'t'- 60 mins]	Downtime [Abnormal Signal] [Avg. minutes] [~'t'- 60 mins]	System Availability	System Availability Average of ~50 Hrs.	Improvement in System Availability using the 2oo2 %Increase, w.r.t 1oo1
2oo2 [ECG-PPG]	[ECG-PPG]	58.2	1.8	97%	95%	62.5%
2oo2 [ECG-PCG]	[ECG-PCG]	54.6	5.4	91.00%	94%	57.8%

6.3 Methodology

In the progression of safety systems design engineering, performed research activities towards aptness usage of safety-related architectures in safety-critical medical systems [200]. We followed a methodology of experimental evaluation by addressing the primary challenges like 1. fault detection in a signal feature computation function during biomedical signal processing, 2. fault-tolerable functionality of the system, and aiming the goals towards:

a) Improving in the elimination of PPG, PCG and ECG-related potential failures in bio-signal detection and removing the deficiencies in signal processing methods to extract the authentic vital sign signal information,

b). Effective predictability in the estimation of illness through data analytics on the authentic vital signal data, which eventually improves in monitoring the subject health and proper nursing,

c) Improve system active time by eliminating much fewer spurious alarms, thus improving the fault tolerability with self-correcting or by using redundancy channel data and thus further improving the system's safety integrity level (SIL) for usage in safety-critical medical applications like medical robotics.

The research activities for this part of the project are divided into mainly three parts:

The first part is dedicated to the study and evaluation of the aptness to use safety-related architectures in the targeted non-invasive diagnostic medical monitoring and to assist control systems in measuring basic vital parameters and identifying suitable sensors for sensing biomedical signals like electric potential, sound, and light.

The second part is devoted to the configurable design and realization of three-independent channels with sensor interface and FPGA-based research prototype for experimental studies.

The final part is dedicated to the calibration of the research platform for safety-critical medical applications (sensor, configurable safety-related architectures, and FPGA design and related circuits) by performing lab and field trials in evaluating the vital parameters like heart rate in addressing the mentioned challenges as reduction of fault alarms, identifying algorithm limitations and improving in uninterruptable system functionality with safe degradation mechanisms.

The part of the experimented results with 2oo2 configuration with 5-configurable concepts is evaluated and presented[236] in Chapter 5. The present chapter focuses on the final part of the research activities in improving the fault detection mechanisms with configurable 2oo3 safety architecture and addressing the challenges using a combination of ECG, PCG and PPG sensor interfaces. In contrast, we used in Chapter 3 and Chapter 4 details of the first and second parts of the system-level research prototype build activities and its preliminary evaluation results.

6.3.1 Instrumentation System Design Overview

The human health monitoring system (HHMS) is designed to be modular and configured to a 2oo3 (2-out-of-3) safety-related computing platform. The integrated system consists of three independent operating channels, as shown in Figure 52 and explained in [200], along with the cardiac health monitoring system (CHMS) GUI tool used in test evaluations.

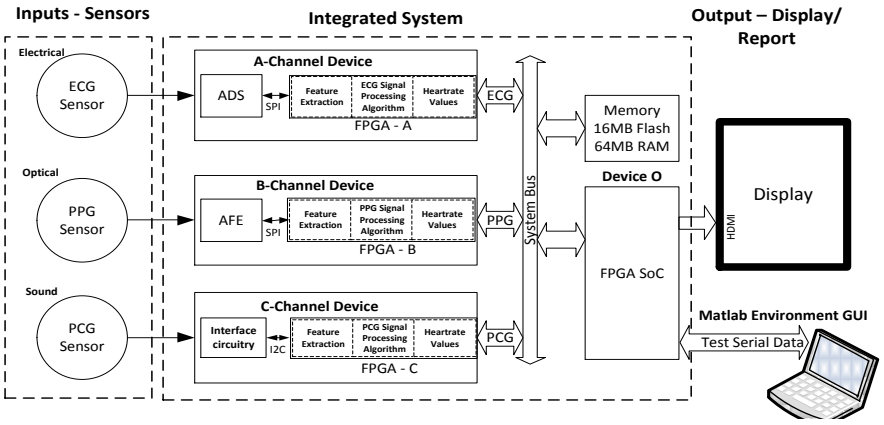


Figure 52: 2oo3 (two-out-of-three) Fault-tolerant Cardiac Health Monitoring System Block Diagram.

6.3.2 Hybrid Sensor (PPG, PCG & ECG) and its configuration

A set of three diverse sensors to sense PPG, PCG, and ECG are selected in three different media, optical, sound, and electrical, respectively, to measure the desired parameter and its related

artifacts from bio-medical signals. The selected PPG sensors (LEDs and detector), PCG sensors (MEMS microphones), ECG sensors (Electric potential Integrated Circuit (EPIC)), and the interfaces used in this 2oo3 system configuration are detailed [200]. These diverse sensors are bonded like a hybrid module into a single package for convenience based on the desired bio-signal parameter monitoring selection. Each sensor module is placed on a subject at the prescribed location for desired parameter measurements. The combinations include ECG-PPG, ECG-PCG, and PPG-PCG, and the selected modules are interfaced to the integrated computing system as shown in Figure 52, configured and evaluated the conceptual 2oo3 safety design.

6.3.3 2oo3 (2-out-of-3) based Safe-Voting Method using correlation analysis

The prototype system must configure 2oo3 with a safe voting mechanism to measure a particular identified vital parametric function. In this system operation approach, the three channels, A, B, and C, receive the sample data and independently compute the vital parameter. Then, as per Table 16 and Figure *53*, these measured values are inputs to the safety function, which correlates and votes to generate the alarm output signal and Fault detection signal. Further, the generated signals trigger the related diagnostic functions to process the data to select the authentic vital output for display and the fault alarm signal. Thus, this mechanism of configuring safe-voting computation shall be performed for each essential parameter measured by the Medical System.

6.3.4 2oo3 (2-out-of-3) Safety-related degradation mechanism

Based on the selected configured parameter in an active system, the System goes into a predefined degradation sequence for any fault detected. These degradation sequences depend on the System's configuration and limitations, such as sensors and availability of the independent processing channels for the same selected parameter. Table 16 shows a few identified vital parameters and their feasible degradation scheme. Since the System is a modular interface and provides high reconfigurability during the System's initial start phase, it either has a high availability system or a high safety System. Thus, we can alter the scheme from 2oo3 to 2oo2 to 1oo1 for high availability with fault-tolerability (or) 2oo2 to 1oo2 to 1oo1 for high safety with fault-tolerability.

Table 16. 2oo3 Configured -System Safe Degradation Scheme.

Vital Sign	FAULT-TOLERANT SYSTEM	Degradation Level				System configuration selection scheme for High Availability or Safety Mode	
		1	2	3	4	High Availability and Fault-tolerant	High Safety and Fault-tolerant
Heart Rate or Pulse	2oo3	2oo2	1oo2	1oo1	Shut down	2oo3 → 2oo2 → 1oo1 →Safe mode	1oo2 →1oo1→ Safe mode
Respiratory Rate	2oo2	1oo2	1oo1	Shut down			
Blood Pressure	2oo2	1oo2	1oo1	Shut down			
Body Temperature	2oo3	2oo2	1oo2	1oo1	Shut down		
Pulse Oximetry	2oo2	1oo2	1oo1	Shut down			

6.3.5 Edge-AI-enabled cause and effect analytics and its prescriptive maintenance suggestions

Edge-AI-based data analytics is performed at three levels: Diagnostics, Prognosis, and Prescriptive. First, as shown in Figure *54* and Figure *58*, the fault data captured during system operating time at each correlated channel -A, -B, -C of Fd(AB), Fd(AC), Fd(BC), and at built-in-tests(BITs) for all identified failure codes as specified in Table 17. In addition, during the prognosis of fault data, considering the severity as conditional weights, the fault data computed for the number of repeated failures that occurred during the system's active time. Finally, the failure data rate meeting the criteria of threshold limits provides the prescriptive maintenance recommendations.

- To do following steps in real-time in 2oo3 configuration, on the measured parameter(p) data from three channels -Channel-A_P (Ch_{Ap}); Channel-B_P (Ch_{Bp}); Channel-C_P (Ch_{Cp});

  For all '□', Ch_{Ap}, $Ch_{Bp,}$ Ch_{Cp}; > >=)
  If (Ch_{Ap} > LL) ∩ (Ch_{Ap} < UL) then
  Ch_A <= True;
  Else
  Ch_A <= False;
  If (Ch_{Bp} > LL) ∩ (Ch_{Bp} < UL) then
  Ch_B <= True;
  Else
  Ch_B <= False;
  If (Ch_{Cp} > LL) ∩ (Ch_{Cp} < UL) then
  Ch_C <= True;
  Else
  Ch_C <= False;

-- for Fault Detection (Fd) :

  If (r_{AB} > 0.5) then
  If (Ch_A XOR Ch_B) then
  $F_{d(AB)}$ <= No-Fault;
  Else
  $F_{d(AB)}$ <= Fault;
  Else
  $F_{d(AB)}$ <= Fault;
  Compute $F_{d(AC)}$ and $F_{d(BC)}$;
  For Fd = $F_{d(AB)}$ OR $F_{d(AC)}$ OR $F_{d(BC)}$;

-- for 2oo3 Alarm Output Signal (O_{Alarm}) :

  If (r_{AB} > 0.5) then
  If (Ch_A OR Ch_B) then
  O_{AB} <= True;
  Else
  O_{AB} <= False;
  Else
  O_{AB} <= False;
  Compute $F_{d(AC)}$ and $F_{d(BC)}$;
  For O_{Alarm} = O_{AB} OR O_{BC} OR O_{AC};

Figure 53: Pseudocode - 2oo3-based Safe-Voting Logical Analytics Using Correlative Technique for Fault Detection and Fault Alarm Output Signal generation.

6.3.6 Experimental setup and System Evaluation

The experimental setup and application protocol detailed in [200] are reused to assess the proposed concept. In addition, the MATLAB-based CHMS GUI tool is used to configure and capture the resultant data to Plot.

Initially, a verified healthy fifty subjects are selected for HR measurements. Well-informed and prepared these subjects per the application protocol[200] and used the monitoring system prototype for evaluation. A set of desired sensory multi-channels or probes are well connected to the subject, and simultaneous readings are logged per CHMS GUI tool configuration. Finally, the experiment is repeated for each subject.

The part of the experiment with 2oo2 configuration with a set of sensor data collected in a combination of ECG-PPG, ECG1-ECG-2, and PPG1-PPG2 evaluated five different concepts and

presented the results[236]. The present chapter focused on the 2oo3 configuration of data, using a partial set of data collected from ECG, PCG, and PPG sensor channels[236] for computation and simultaneous failure signal data for AI analytics on prescriptive maintenance.

Table 17. 2oo3 based Cause and Effect - Fault Diagnostics & Evaluation Analytics and prescriptive inferences for the identified cause.

Evaluation cases [Case-1 to Case 64]	Ch -A	Ch -B	Ch -C	X	Y	Z	O	R	Code	Severity	Fault description & Probable cause	Prescriptive maintenance inferences for the identified causes.
Case-1	T	T	T	T	T	T	T	N	SwAgF 4001	No-Fault	Data Authentic	No action
Case-2 to Case-8	T	T	T	T/ F	T/ F	T/ F	T/ F	Y	SwAgF 4002 to 4008	Major/ Minor	May be Software Sync/Delay issue between Channels-A,B; A,C; B,C Negligible higher pulse count detected in ECG, PCG	➢ Primary Issues of failures: ▪ Sensing Probe failure of ECG/PCG/PPG. ▪ Signal Bias issues to detect the signal. ▪ Sync/Delay Issue between channels. ▪ Algorithm computation delay issues between channels. ➢ Overall failure analysis Hardware and software issues segregation like display module, cuff, Sensor, Calibration, Battery, power supply, Probe, Connector, and Other unknown issues.
Case-9 to Case-16	T	T	F	T/ F	T/ F	T/ F	T/ F	Y	SwAgF 4009 to 4016	Major/ Minor	Possible cause in Software or Hardware issues at channels A, B; B, C, and A, C	
Case-17 to Case-32	T	T/ F	T/ F	T/ F	T/ F	T/ F	T/ F	Y	SwAgF 4017 to 4032	Critical	Data Authentic Software Sync/Delay Issue between channels (or) Negligible higher pulse count detected in PPG & PCG	
Case-33 to Case-40	F	T	T	T/ F	T/ F	T/ F	T/ F	Y	SwAgF 4033 to 4040	Critical	Possible cause in Software or Hardware issues at channels A, B; B, C, and A, C	
Case-41 to Case-64	F	T/ F	T/ F	T/ F	T/ F	T/ F	T/ F	Y	SwAgF 4041 to 4064	Critical	Data Authentic Software Sync/Delay Issue between channels (or) Negligible higher pulse count detected in ECG & PPG	

Where Ch-A: Channel-A (ECG) [Parameter within set limits then TRUE else False]
Ch-B: Channel-B (PPG) Parameter within set limits then TRUE else False]
Ch-C: Channel-C (PCG) Parameter within set limits then TRUE else False]
X: Correlation coefficient ‘r’ measured between ECG-PPG, if r(>0.5) then TRUE else False.
Y: Correlation coefficient ‘r’ measured between ECG-PCG, if r(>0.5) then TRUE else False.
Z: Correlation coefficient ‘r’ measured between PPG-PCG, if r(>0.5) then TRUE else False.
O: 2oo3 Fault tolerant Output Signal Alarm[True-No Alarm; False-Alarm]
R: Result = Fault Diagnostics required for Detected Failure = Yes or No
Code: Software functional Fault/Negation codes
[SW-Software; Ag-Algorithm; F-Function; [4-digit] – Code]
Severity: Fault Severity Analysis No-Fault/Minor/Major/Critical
[Algorithm function analysis metric]
T: True; F: False; Y: Yes; N: No;

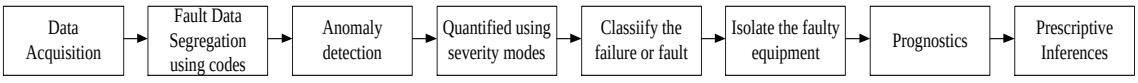


Figure 54: Framework workflow for Edge-AI-based fault data analytics for prescriptive maintenance.

6.4 Experimental Results and Discussion

The System configured with 1oo1 and captured HR data values Vs. Fault alarm signals individually as ECG-1oo1, PPG-1oo1, and PCG-1oo1 are presented in Figure *38*, Figure *39*, and Figure *55* from a single subject. The captured alarm data is analyzed to set configurable adjustable upper and lower limits (ADJ-UL & LL) [200].

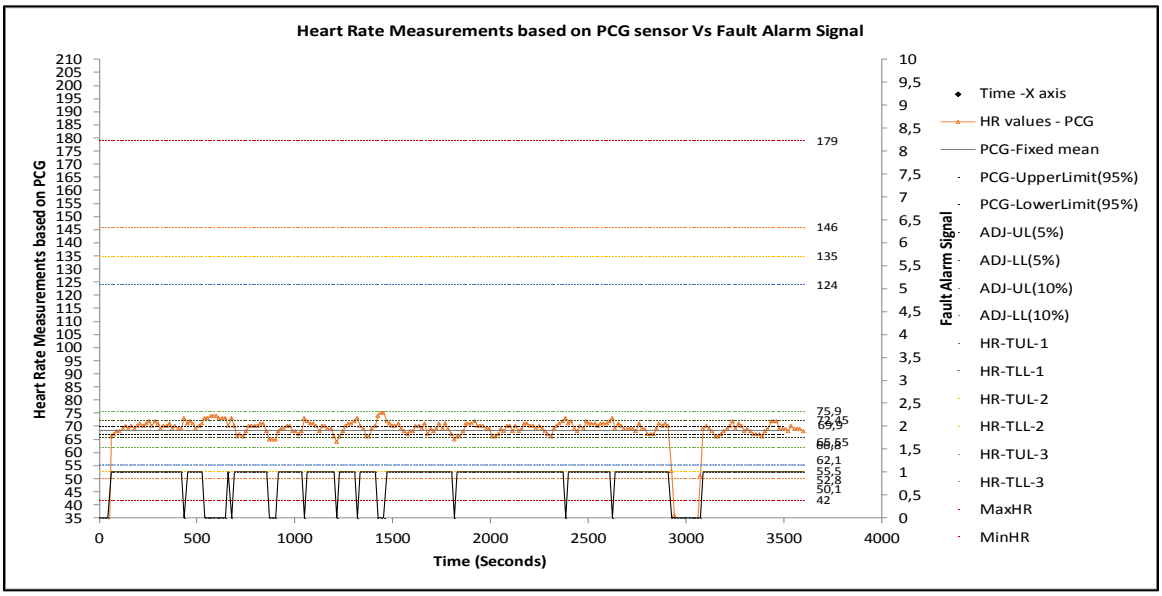


Figure 55: Heart Rate Measurement based on PCG sensor Vs. Fault Alarm signal in 1oo1 configuration.

The captured correlation signals ECG-PCG, ECG-PPG, and PCG-PPG Vs. a fault alarm signal are shown in respective Figure *42*, Figure *56*, and Figure *57*. It analyzed that the reduction of alarm readings from all fifty subjects (with an overall 200 Hrs monitoring) is similar in meeting the objectives. Figure *58* present the configured 2oo3- results of a single subject, which shows the reduction in alarms and its related cause & effect evaluated analysis presented in Table 17 with inferences.

The sensor's ECG, PCG, and PPG processed signal data are captured and performed analytics using MATLAB tool by configuring the system in 2oo3 configuration. The tool computes system uptime and downtime by separating the normal and abnormal signal data, as shown in Figure *59*. Figure *60* shows the prescriptive results of the failure recorded data of the power supply and sensor probes using computed edge-AI workflow.

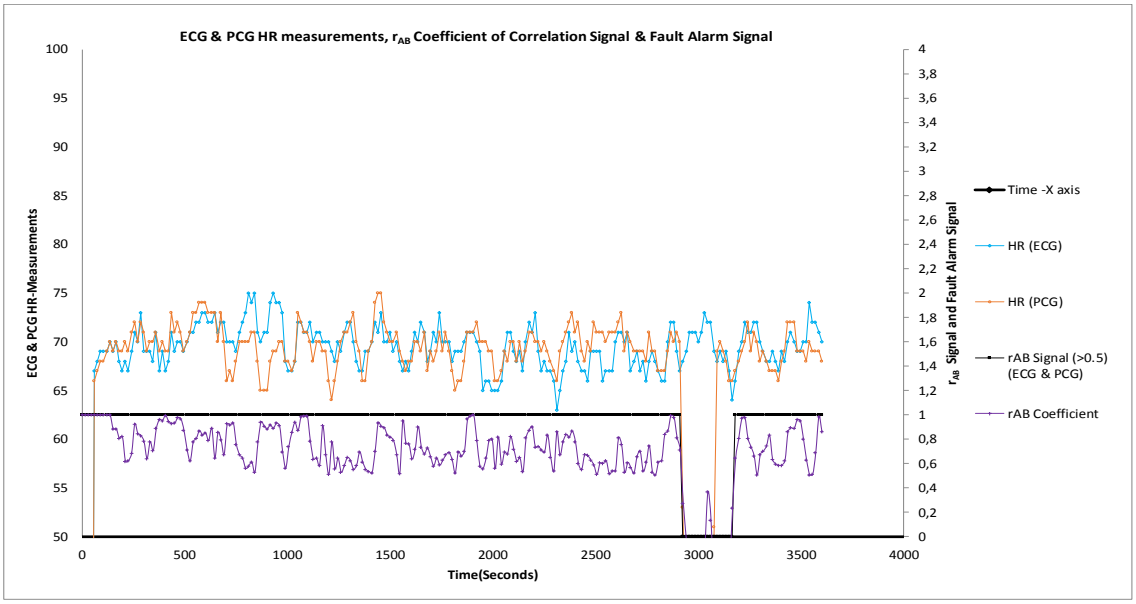


Figure 56: ECG & PCG Heart Rate Measurements, r_{AB} Coefficient of Correlation signal Vs. Fault Alarm signal

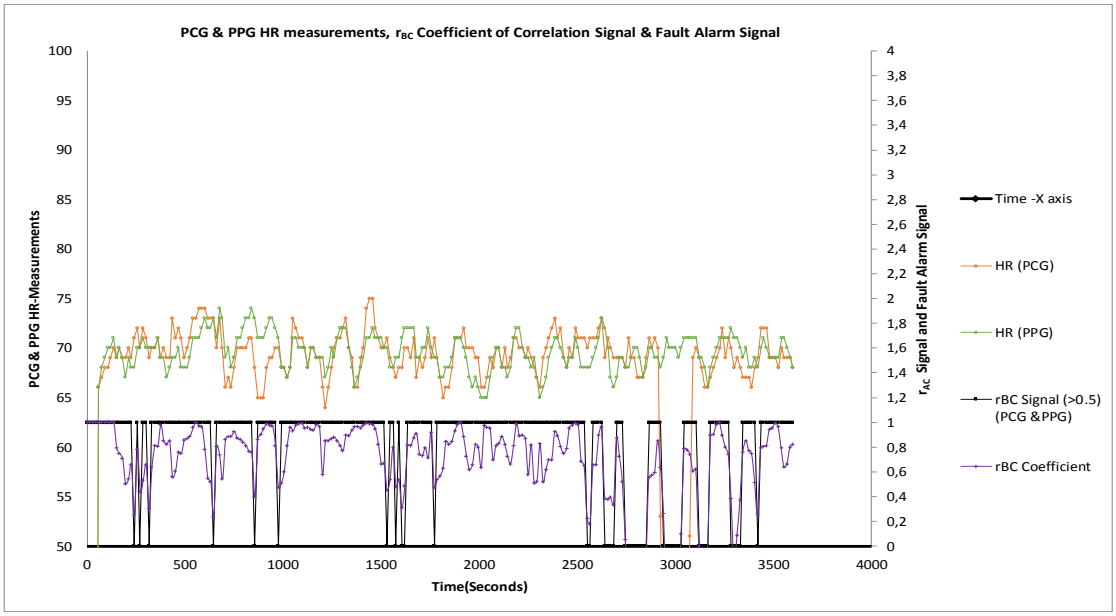


Figure 57: PCG & PPG Heart Rate Measurements, r_{BC} Coefficient of Correlation signal Vs. Fault Alarm signal.

Following the Declaration of Helsinki(1964), informed consent has been taken from fifty subjects in the age group of 15 -55 years. The monitoring system evaluated fifty subjects of various age groups with a record captured in four hours per subject in succession at the same

conditions and following application protocol[200] and recorded the uptime and downtime of the system during evaluation. As a result, an average of 200 Hrs total operating time of the system and calculated system availability in percentile as per equation-1. Table 17 provided these results along with system health inferences computed as per negation codes specified in Table 17 and assessed in the set configuration that the improvement in system availability significantly improved from 85 % to 98%.

However, to validate the improvement function at the system level resilience, more tests must be performed with various sensors to evaluate function performance better. It has been observed that during experimentation, limitations exist, such as mainly a signal drift issue during capture, and an appropriate sync mechanism needs to improve between the signals and channels. The drift of +/- 2 pulses was noticed as a system's limitation due to different sensor media of operation, capturing, and measurement periods. Further noticed, the system response time is less than <5 seconds as a limitation. However, a detailed analysis of the uptime period of signals confirms that the count of truthful pulses in correlated channels is almost the same during long-term signal capture with negligible or no incorrect pulses and un-detected pulses recorded. In contrast, it can mitigate drift issues during short-term signal capture in the design by improving the synchronization mechanism for capturing the signals between the channels.

Further investigation on the uptime and down signals helps understand the causes of various systemic faults within the sensor system. The related fault data is captured, analyzed, and provided inferences in Table 17. Additional analysis of this corresponding prognostic health data is out of this chapter's scope as it requires defining normal or abnormal vital parameter signal classification and identifying support mechanisms within the system. In this chapter, as we focused on the system's health and availability with reduced alarms by processing the signal data and evaluating the safety function, we used only minimal conditions to infer the system's health.

The presented experimental data is captured from each channel with HR-measured data. In addition, the alarm signal's inverted logic level is logged for the 1-hour Avg. duration per subject, considered for evaluating the System. The analysis results show significant improvements in meeting the objectives and a similar systematic approach to further apply this method to other parameter evaluations for safety improvements.

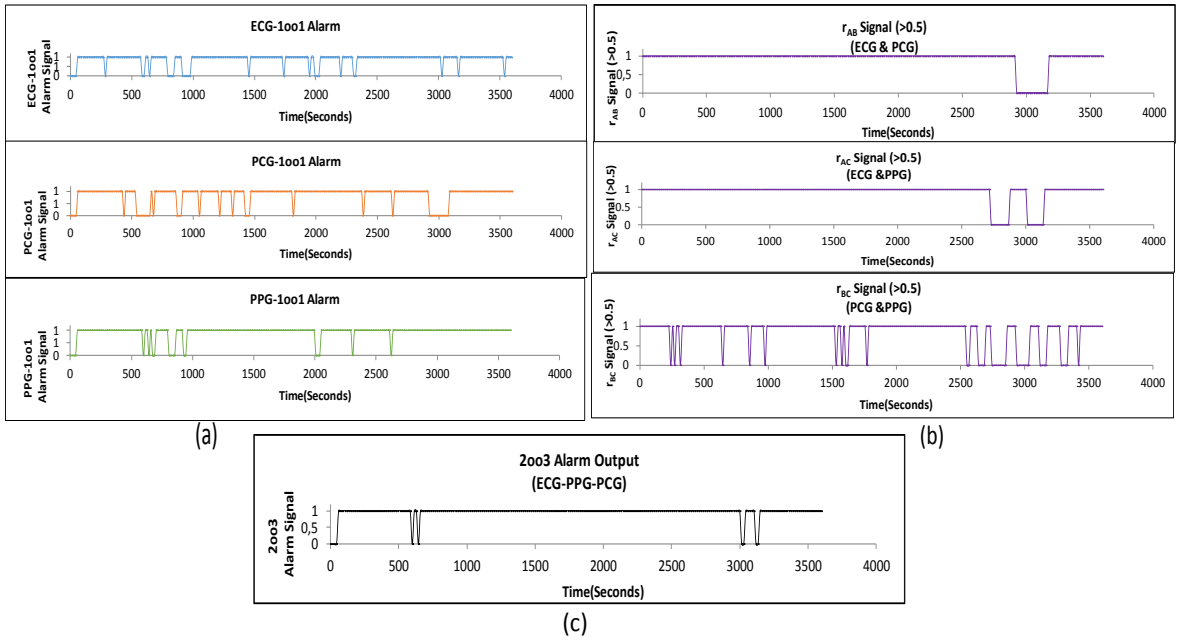


Figure 58: (a) Fault Alarm output recorded at each channel A, B, and C during Heart rate monitoring in 1 hour. (b) Correlative Signal Record between channels ECG-PCG, ECG-PPG, and PCG-PPG during Heart rate monitoring in 1 hour. (c) 2oo3 configured system Fault Alarm output during Heart rate monitoring in 1 hour.

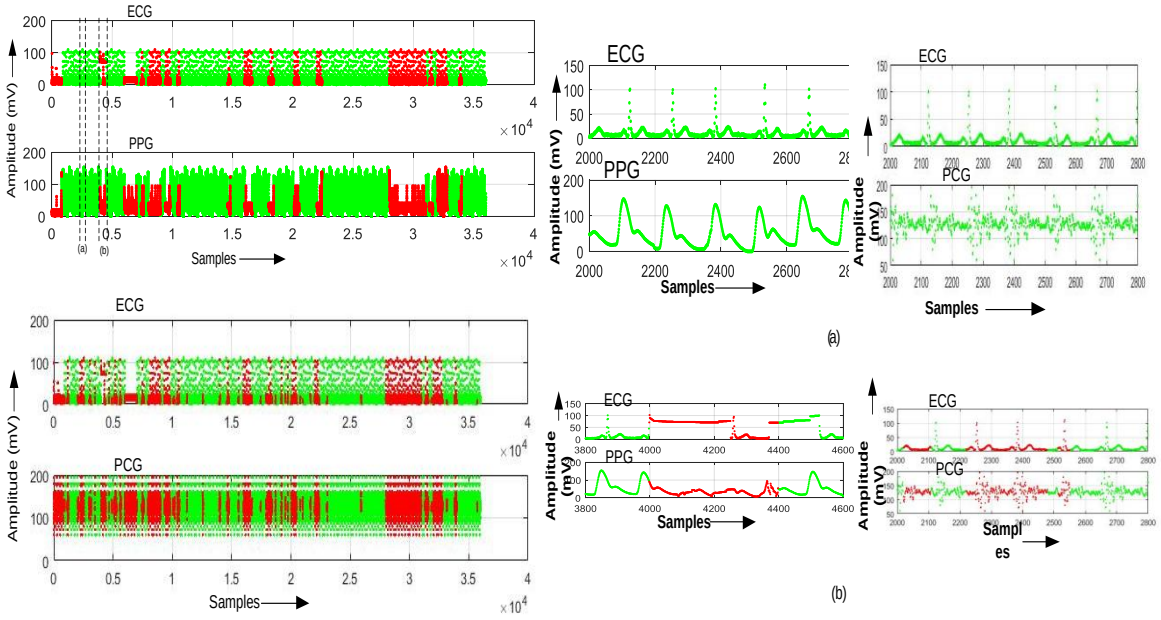


Figure 59: ECG, PCG, PPG processed signals data captured using MATLAB tool w.r.t 2oo3 configuration (a) System Uptime – Normal signal data with no-fault (Green). (b) System Downtime – Abnormal signal data with a fault (Red)

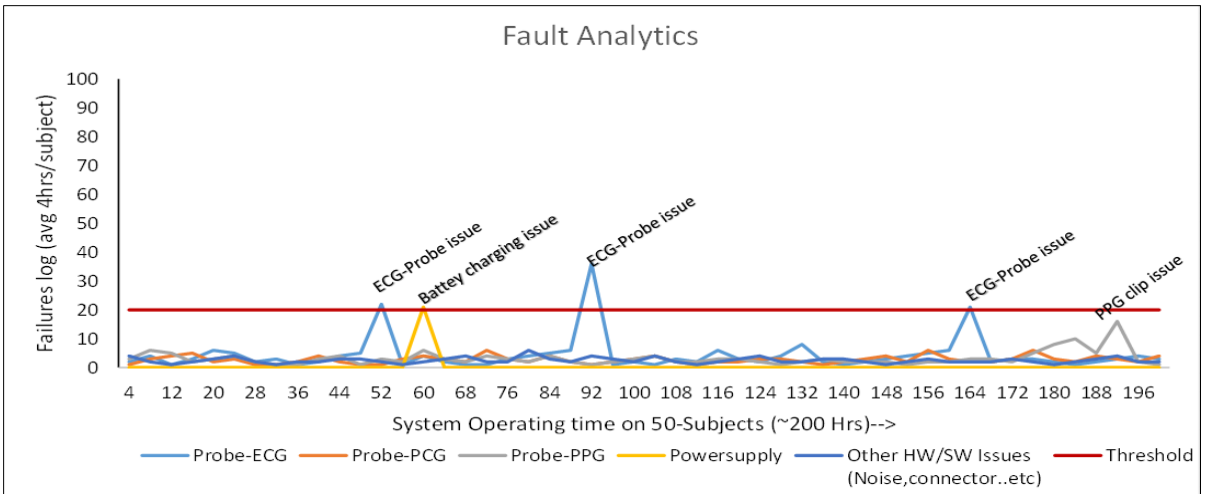


Figure 60: Edge-AI-enabled fault data analytics and its prescriptive maintenance recommendation

Table 18. System Operational Availability Results by Configuring the Fault-tolerant Medical Instrumentation System in 2oo3 (2-out-of-3) configuration mode.

Fault-tolerant System Configuration In TMR or 2oo3(2-out-of-3) mode	**Signals**	**Up-time [Normal Signal] [Avg. minutes] [~'t'- 60 mins]**	**Downtime [Abnormal Signal] [Avg. minutes] [~'t'- 60 mins]**	**System Availability configuration**	**System Availability Average of ~200 hrs**	**Improvement in System Availability using the 2oo3 design approach %Increase (approx.)**	**Data Analytics Inferences on System Health – Common Causes**
System Evaluation performed using 50 Subjects with data record Four hours/subject and an average of 1 hour.	Channel-A [ECG]	53.4	6.6	89%	90%	20%	Main Hardware causes: • ECG, PPG, and PCG Sensor probe contact fault. • Power-related faults. Main Software causes: • Data Sync delay Issues between channels due to algorithm computation times • Inaccuracy in detecting the pulses mainly due to causes of Noise and feeble pulses.
	Channel-B [PCG]	46.8	13.2	78%	76.2%		
	Channel-C [PPG]	55.2	4.8	92%	89%		
	2oo3 Fault-tolerant-Output [ECG-PCG-PPG]	59.4	0.6	99%	98.6%		

Further, the CHMS is evaluated for reliability by measuring the System level MTBF, Repeatability, and Reproducibility parameters. Table 18 presents the results. The higher MTBF value of 28.40 shows improvement from the 1oo1 and -2oo2 system. Following the application protocol, experimental system evaluation is performed for repeatability and reproducibility. Table 19 shows that the measured values have less variance when compared to the 1oo1 and -2oo2 systems. However, the considered limitation is complexity, which increases further in -2oo3, and following a systematic design approach and guidelines may further help reduce the limitations in complexity.

Table 19: 2oo3 Configured CHMS MTBF, Repeatability and Reproducibility Results

Configuration Type	Sensor channel	MTBF [~ minutes]	MTTF [~ minutes]	Repeatability of CHMS (SD)	Repeatability of CHMS (SDM)	Reproducibility of CHMS
1oo1	ECG	3.31	3.31	2.16	0.68	0.07
1oo1	PCG	6.53	6.53	1.52	0.48	1.63
1oo1	PPG	28.40	28.40	1.20	0.37	0.79
2oo2	ECG-PPG	28.40	Not applicable to a reparable system.	1.20	0.38	0.14
2oo2	ECG-PCG	24.60		1.70	0.54	0.79
2oo3	[ECG - PCG - PPG]	28.40		1.20	0.38	0.14

6.5 Conclusion

In this chapter, a concept of fault-tolerant safety-related two-out-of-three(2oo3) or TMR design approach implemented and evaluated in the configurable medical cardiac health monitoring system, a research platform, addresses the effective detection of functional faults improving the uninterruptable function of the targeted medical System by reducing the false or spurious alarms. This framework has significantly reduced the generation of insignificant alarms and increased uninterruptable System availability by 85% to 98%. These findings and the design approach are important contributions to issues related to present medical patient monitoring systems without significant impact on cost since they use the existing system configuration of ECG, PCG, and PPG signals along with FPGA technology devices. While we have focused on eliminating identified issues, the conceptual design approach may suit medical monitoring systems, implying that our findings are likely necessary for designing medical monitoring and control systems. Further, the measured MTBF results for CHMS show improvement in reliability in 2oo3 configuration and less variance in results of repeatability and reproducibility. In terms of future research, we suggest using diverse algorithms and sensors (or) evaluation with a combination of these with effective predictive system maintenance, which helps eliminate spurious alarms with reduced downtime of the system and produce more accurate data vital parameters.

Chapter 7. Conclusion

7.1 Summary of the present work

It is essential to monitor the pathophysiological state of an individual uninterruptedly during critical times by measuring authentic vital parameters, which provides insights for predicting imminent health hazards.

Portable, non-invasive human health monitoring systems like PMS, POCTs one of the popular research areas that aim at the development of low-cost, reliable, and accurate monitoring systems to use in critical times by improving the safety parameters like Availability – i.e., improvement in systems operational uptime, Reduction of Alarms – i.e., reducing spurious alarms, improvement in segregating the authentic data from abnormal data to compute prognostics for better medication. These systems help in building a healthier society as day by day, more and more populations are being effected by various health issues caused due to abnormal levels of monitoring of human health vitals at critical times.

Various design approaches have been proposed in the literature, like hot/warm standby, Cold stand-by, FFIP, FCC, etc. Many research groups are exploring a wide variety of design approaches to develop a system that can provide an improvement in safety and reliable results conveniently and economically.

Chapter 3 detailed the safety-related architectures 1oo1-, 1oo2-, 2oo2- and 2oo3- and describes their apt usage in developing the CHMS instrument prototype with three independent channels based on ECG, PPG and PCG. It has provided the details of the correlation method used in safe logic development, experimental set-up, and evaluation framework. An application protocol has been described and followed to capture the sample data and evaluated using GUI based CHMS configuration tool developed based on MATLAB software. Finally, an experimental case study has been presented by configuring the CHMS system in 2oo2 using two independent channels of ECG and PCG. It has been observed that the results show improvements in the reduction of spurious alarms significantly by more than 85% to 95%. Further, we evaluated the reliability of the CHMS prototype by measuring the MTBF, MTTF, Repeatability, and Reproducibility parameters of each independent channel as well as the configured -2oo2 and -2oo3 architectures and presented the operational Availability results.

Chapter 4 described developing and optimizing a fault-tolerant human health monitoring system based on 2oo2 architecture using ECG and PPG channels to effectively separate authentic data from system-level failures. Evaluated the functions such as AND-OR safety function, correlation-based safe function, and fuzzy entropy-based detection technique are used for the vital measured in terms of positive predictive values (PPV) and sensitivity (Se) on authentic data. It has been observed that the segregation of normal data from abnormal data is effective and computed with positive predictive values (PPV) of nearly 99.99%, whereas sensitivity (Se) of the ECG channel is greater than 99.97% and 99.95% for the PPG channel.

Chapter 5 detailed the improvement parameters like systems availability and developed an authentic measure of vital sign HR using a fault-tolerant design approach with safety analysis using 2oo2 architecture using independent channels ECG and PPG. Evaluated the safe functions and five different concepts in various diverse modes and presented a cause and effect analysis. It has been observed that a significant improvement of 55% to 95% in the reduction of spurious alarms is achieved and improved the system's availability by 45% to 55%.

Chapter 6 detailed the enhancements of safety analytics using an edge-AI-enabled triple module redundancy design approach using three independent channels, ECG, PPG, and PCG, to improve systems availability parameters. The safe functions and safe degradation mode were evaluated and a cause and effect analysis presented. It has been observed that a significant improvement by greater than 95% in the reduction of spurious alarms is achieved and improved the system's availability by greater than 95%.

Based on the availability of multimodal sensor configurations, the system can be configured at once for the desired mode in 2oo2 or 2oo3 for each vital measurement. The cost of using reagents constitutes a substantial portion of the operating expenses.

The current research focuses on using safety-related design architectures for non-invasive HHMS, PMS, and PCOT devices, mainly to segregate the authentic data from abnormal data of the various systemic failures and system availability improvement. A correlative technique is used in the existing safety-related design architectures to achieve the objectives, and both qualitative and quantitative analysis are used to separate the systemic failure data from human health vital data, and normal authentic vital data is segregated from abnormal data.

7.2 Conclusion

Safety Medical systems with intelligence are one of the demanding research areas that aim to develop reliable and accurate medical diagnostic systems at a lower cost with portability. Furthermore, these safety systems help build a healthier society by providing reliable inputs to healthcare providers for better nursing, to the patients with predictive alerts on their ill health, and device health inputs for the owners for better operability by saving costs.

Various methods to improve safety in the system design life cycle have been proposed in the literature. Many research groups are exploring various approaches to develop a device that can provide stable and reliable results conveniently and economically. As technology improves, many research groups are constantly working on these problems in medical monitoring systems to find a better way to solve them. For example, they are trying to reduce the number of false alarms, improve the accuracy of vital signs, and use health artifacts to predict illness before it happens. They also use PdM and PPM techniques to improve the system's operational time availability with fault tolerability.

The current research focuses on using safety-related architectures in the design of medical systems, such as safe correlative computations. However, many problems with biosignal detection need to be addressed, including a lack of accurate data for predicting illness and a lack of reliability in the system's operation. This study aims to identify the root causes of these issues so that they can be mitigated and the system can operate more reliably. A CHMS prototype is built and can be configurable to operate in 2oo2 and 2oo3 approaches, along with fault-tolerant functions used in the quantitative analysis. Here, we have investigated and analyzed the recorded failure output data towards the reliability and efficiency of the implemented algorithmic software function and provided the inferences on improvements at the systems level requirements. Thus, a practical heart rate (HR) computing function is realized in both channels (i.e., in the 2oo2 approach) with authentic heart rate output for prognostic diagnostics with reduced alarms, i.e., we effectively segregated the faulty or an abnormal signal.

Further, a system configured with one sensor interfacing with both channels, with the same algorithmic function for computation. Again, this configurable analysis provided the opportunity to investigate the safety functions' response to its improvements in defining the requirements. Thus, this approach helps to evaluate system-level hardware and software failure analysis. Finally, as part of an extended experiment, we collected the data in 2oo3 CHMS system

configuration using three diverse sensors: ECG, PPG, and PCG. The data is evaluated for the overall system availability, and the collected failure data is analyzed based on edge-AI-based prescriptive maintenance of the system.

Thus, based on this experimental research, by design and developing a research CHMS prototype having known limitations of FPGA and configurability of channels. Overall, the experiment was carried out for more than 200 Hrs with the selected and tested 50 - healthy subjects from different age groups. As a result, we have concluded, as part of this research, such as:

- Using fault-tolerant design architectures in medical systems, observed that in the 2oo2 configuration, the system availability improved by 45% to 55%, and in the 2oo3 configuration further improved by approximately 85% to 95%.
- A significant improvement by approx. 55% to 95% in the reduction of spurious alarms in both 2oo2 and 2oo3 configurations when compared to the 1oo1 configuration of the system.
- A significant improvement by average. Approx. >95% in the authentic vital parameter (HR used in the experiments) measured in 2oo2 and 2oo3 configurations when compared to the 1oo1 configuration of the system.
- Evaluated the failure data w.r.t abnormal signal, and the implemented edge-AI enabled analytics on the selected fault codes, showing promising results with prescriptive maintenance inferences.

7.3 Scope of future work

In the recent past, many design architectures and approaches have been followed for improvement in the safety of the monitoring systems. However, none of these design approaches have produced a clinically reliable system with fewer spurious alarms and more system availability. Although extensive research is being done, it is understood that it is a continuous improvement activity in safety, specifically the critical health monitoring systems in ICU usage.

It has been achieved that safety-related design architectures are quite useful in developing human health monitoring systems with significant improvements in availability and reduction of spurious alarms. Now, there is a scope for improving the system safety on systems components using the system's abnormal data.

In the recent past, based on the incorporated technologies in the systems, the systems underwent preventive and periodic maintenance. However, providing the requisite safety with ergonomics value is not easy. Moreover, with the advancements in AI usage, work has to be done in-depth on these segregated normal data for a better prognosis of diseases such as HD, CVDs, and other illnesses. Further work needs to be carried out on predictive maintenance of the system.

Bibliography

[1] Avent RK, Charlton JD. A critical review of trend-detection methodologies for biomedical monitoring systems. Crit Rev Biomed Eng. 1990;17(6):621-59. PMID: 2180635.

[2] P. Varady, Z. Benyo and B. Benyo, "An open architecture patient monitoring system using standard technologies," in IEEE Transactions on Information Technology in Biomedicine, vol. 6, no. 1, pp. 95-98, March 2002, doi: 10.1109/4233.992168

[3] Custodio, V., Herrera, F.J., López, G. and Moreno, J.I., 2012. A review on architectures and communications technologies for wearable health-monitoring systems. Sensors, 12(10), pp.13907-13946.

[4] Drews FA. Patient Monitors in Critical Care: Lessons for Improvement. In: Henriksen K, Battles JB, Keyes MA, et al., editors. Advances in Patient Safety: New Directions and Alternative Approaches (Vol. 3: Performance and Tools). Rockville (MD): Agency for Healthcare Research and Quality (US); 2008 Aug. Available from: https://www.ncbi.nlm.nih.gov/books/NBK43684/

[5] Özcan, E., Birdja, D., Simonse, L. and Struijs, A., 2019. Alarm in the ICU! Envisioning patient monitoring and alarm management in future intensive care units. Service Design and Service Thinking in Healthcare and Hospital Management, pp.421-446.

[6] Paradiso, R., 2003, April. Wearable health care system for vital signs monitoring. In 4th International IEEE EMBS Special Topic Conference on Information Technology Applications in Biomedicine, 2003. (pp. 283-286). IEEE.

[7] Kyriacos, U., Jelsma, J. and Jordan, S., 2011. Monitoring vital signs using early warning scoring systems: a review of the literature. Journal of nursing management, 19(3), pp.311-330.

[8] Elliott, M. and Coventry, A., 2012. Critical care: the eight vital signs of patient monitoring. British Journal of Nursing, 21(10), pp.621-625.

[9] Rose, L. and Clarke, S.P., 2010. Vital signs. AJN The American Journal of Nursing, 110(5), p.11.

[10] Evans, D., Hodgkinson, B. and Berry, J., 2001. Vital signs in hospital patients: a systematic review. International journal of nursing studies, 38(6), pp.643-650.

[11] Graham, K.C. and Cvach, M., 2010. Monitor alarm fatigue: standardizing use of physiological monitors and decreasing nuisance alarms. American Journal of Critical Care, 19(1), pp.28-34.

[12] Ebert, C., 2015. Implementing functional safety. IEEE Software, 32(5), pp.84-89.

[13] Sklyar, V., 2017. Application of reliability theory to functional safety of computer control systems. Reliability: Theory & Applications, 12(1 (44)).

[14] H. Alemzadeh, R. K. Iyer, Z. Kalbarczyk and J. Raman, "Analysis of Safety-Critical Computer Failures in Medical Devices," in IEEE Security & Privacy, vol. 11, no. 4, pp. 14-26, July-Aug. 2013. DOI: 10.1109/MSP.2013.49

[15] Baig, M.M., Gholamhosseini, H. and Connolly, M.J., 2013. A comprehensive survey of wearable and wireless ECG monitoring systems for older adults. Medical & biological engineering & computing, 51(5), pp.485-495.

[16] Morik, K., Brockhausen, P. and Joachims, T., 1999. Combining statistical learning with a knowledge-based approach: a case study in intensive care monitoring (No. 1999, 24). Technical Report.

[17] Grout, J.R., 2003. Preventing medical errors by designing benign failures. The Joint Commission Journal on Quality and Safety, 29(7), pp.354-362.

[18] Wallace, D.R. and Kuhn, D.R., 1999, November. Lessons from 342 medical device failures. In Proceedings 4th IEEE International Symposium on High-Assurance Systems Engineering (pp. 123-131). IEEE.

[19] Reason, J., 1995. Understanding adverse events: human factors. BMJ Quality & Safety, 4(2), pp.80-89.

[20] Rothschild, J.M., Landrigan, C.P., Cronin, J.W., Kaushal, R., Lockley, S.W., Burdick, E., Stone, P.H., Lilly, C.M., Katz, J.T., Czeisler, C.A. and Bates, D.W., 2005. The Critical Care Safety Study: The incidence and nature of adverse events and serious medical errors in intensive care. Critical care medicine, 33(8), pp.1694-1700.

[21] Pietzsch, J.B., Shluzas, L.A., Paté-Cornell, M.E., Yock, P.G. and Linehan, J.H., 2009. Stage-gate process for the development of medical devices. Journal of Medical Devices, 3(2).

[22] Sipos, R., Fradkin, D., Moerchen, F. and Wang, Z., 2014, August. Log-based predictive maintenance. In Proceedings of the 20th ACM SIGKDD international conference on knowledge discovery and data mining (pp. 1867-1876).

[23] Hauser, R.G., Mugglin, A.S., Friedman, P.A., Kramer, D.B., Kallinen, L., McGriff, D. and Hayes, D.L., 2012. Early detection of an underperforming implantable cardiovascular device using an automated safety surveillance tool. Circulation: Cardiovascular Quality and Outcomes, 5(2), pp.189-196.

[24] Johnson, T.R., Thimbleby, H., Killoran, P. and Diaz-Garelli, J.F., 2015. Human Computer Interaction in Medical Devices. In Cognitive Informatics for Biomedicine (pp. 163-187). Springer, Cham.

[25] Dias, D. and Paulo Silva Cunha, J., 2018. Wearable health devices—vital sign monitoring, systems and technologies. Sensors, 18(8), p.2414.

[26] Adithya, P.C., Sankar, R., Moreno, W.A. and Hart, S., 2017. Trends in fetal monitoring through phonocardiography: Challenges and future directions. Biomedical Signal Processing and Control, 33, pp.289-305.

[27] Kubicek, J., Fiedorova, K., Vilimek, D., Cerny, M., Penhaker, M., Janura, M. and Rosicky, J., 2020. Recent Trends, Construction and Applications of Smart Textiles and Clothing for Monitoring of Health Activity: A Comprehensive Multidisciplinary Review. IEEE Reviews in Biomedical Engineering.

[28] Eldridge, B., Gruben, K., LaRose, D., Funda, J., Gomory, S., Karidis, J., McVicker, G., Taylor, R. and Anderson, J., 1996. A remote center of motion robotic arm for computer assisted surgery. Robotica, 14(1), pp.103-109.

[29] Guiochet, J. and Vilchis, A., 2002, October. Safety analysis of a medical robot for tele-echography. In 2nd IARP IEEE/RAS joint workshop on Technical Challenge for Dependable Robots in Human Environments, Toulouse, France.

[30] Kazanzides, P., 2009, September. Safety design for medical robots. In 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 7208-7211). IEEE.

[31] Kebe, M., Gadhafi, R., Mohammad, B., Sanduleanu, M., Saleh, H. and Al-Qutayri, M., 2020. Human vital signs detection methods and potential using radars: A review. Sensors, 20(5), p.1454

[32] Avgousti, S., Christoforou, E.G., Panayides, A.S., Voskarides, S., Novales, C., Nouaille, L., Pattichis, C.S. and Vieyres, P., 2016. Medical telerobotic systems: current status and future trends. Biomedical engineering online, 15(1), pp.1-44.

[33] Boulemtafes, A. and Badache, N., 2016. Design of wearable health monitoring systems: An overview of techniques and technologies. mHealth Ecosystems and Social Networks in Healthcare, pp.79-94.

[34] Yager, P., Domingo, G.J. and Gerdes, J., 2008. Point-of-care diagnostics for global health. Annu. Rev. Biomed. Eng., 10, pp.107-144.

[35] Finch, A.S., Bickford, J.R., Conn, M.A., Coppock, M.B., Sarkes, D.A. and Stratis-Cullum, D.N., 2013, May. Towards a modular, robust, and portable sensing platform for biological and point of care diagnostics. In Smart Biomedical and Physiological Sensor Technology X (Vol. 8719, p. 87190P). International Society for Optics and Photonics.

[36] Wang, P. and Kricka, L.J., 2018. Current and emerging trends in point-of-care technology and strategies for clinical validation and implementation. Clinical chemistry, 64(10), pp.1439-1452.

[37] Vashist, S.K., 2017. Point-of-care diagnostics: Recent advances and trends. Biosensors, 7(4), p.62.

[38] Ferryanto, L., Peer Reviewed: Medical Devices.

[39] Shafik, R.A., Das, A., Yang, S., Merrett, G. and Al-Hashimi, B.M., 2015. Design considerations for reliable embedded systems. Reliability Characterisation of Electrical and Electronic Systems, pp.169-194.

[40] Fairbanks, R.J. and Caplan, S., 2004. Poor interface design and lack of usability testing facilitate medical error. The Joint Commission Journal on Quality and Safety, 30(10), pp.579-584.

[41] Dhillon, B.S., 2003. Human reliability and error in medical system (Vol. 2). World Scientific.

[42] Tsai, W.T., Mojdehbakhsh, R. and Rayadurgam, S., 1997, August. Experience in capturing requirements for safety-critical medical devices in an industrial environment. In Proceedings 1997 High-Assurance Engineering Workshop (pp. 32-36). IEEE.

[43] Lubaszewski, M. and Courtois, B., 1998. A reliable fail-safe system. IEEE Transactions on Computers, 47(2), pp.236-241.

[44] Joseph, A., Henriksen, K. and Malone, E., 2018. The architecture of safety: An emerging priority for improving patient safety. Health Affairs, 37(11), pp.1884-1891.

[45] Beneyto, A., Bequette, B.W. and Vehi, J., 2021. Fault Tolerant Strategies for Automated Insulin Delivery Considering the Human Component: Current and Future Perspectives. Journal of Diabetes Science and Technology, p.19322968211029297.

[46] Israelski, E.W. and Muto, W.H., 2004. Human factors risk management as a way to improve medical device safety: a case study of the therac 25 radiation therapy system. The Joint Commission Journal on Quality and Safety, 30(12), pp.689-695.

[47] Harrison, M.D., Freitas, L., Drinnan, M., Campos, J.C., Masci, P., di Maria, C. and Whitaker, M., 2019. Formal techniques in the safety analysis of software components of a new dialysis machine. Science of Computer Programming, 175, pp.17-34.

[48] Baura, G., 2011. Medical device technologies: a systems based overview using engineering standards. Academic Press.

[49] Bakhshi, R., Kunche, S. and Pecht, M., 2014. Intermittent failures in hardware and software. Journal of Electronic Packaging, 136(1).

[50] Khalil, K., Eldash, O., Kumar, A. and Bayoumi, M., 2020. Machine learning-based approach for hardware faults prediction. IEEE Transactions on Circuits and Systems I: Regular Papers, 67(11), pp.3880-3892.

[51] Authén, S., Gustafsson, J. and Holmberg, J.E., 2012. Guidelines for reliability analysis of digital systems in PSA context-Phase 2 Status Report.

[52] Fei, B., Ng, W.S., Chauhan, S. and Kwoh, C.K., 2001. The safety issues of medical robotics. Reliability Engineering & System Safety, 73(2), pp.183-192.

[53] Sanchez, L.A., Le, M.Q., Rabenorosoa, K., Liu, C., Zemiti, N., Poignet, P., Dombre, E., Menciassi, A. and Dario, P., 2013. A case study of safety in the design of surgical robots: The ARAKNES platform. In Intelligent Autonomous Systems 12 (pp. 121-130). Springer, Berlin, Heidelberg.

[54] Li, Q., Alemzadeh, H., Kalbarczyk, Z. and Iyer, R.K., 2015, May. A fault-tolerant hardware architecture for robust wearable heart rate monitoring. In 2015 9th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) (pp. 185-192). IEEE.

[55] Voas, E., Charron, F., McGraw, G., Miller, K. and Friedman, M., 1997. Predicting how badly" good" software can behave. IEEE Software, 14(4), pp.73-83.

[56] Nascimento, A.S., Rubira, C.M., Burrows, R. and Castor, F., 2013, April. A systematic review of design diversity-based solutions for fault-tolerant soas. In Proceedings of the 17th

International Conference on Evaluation and Assessment in Software Engineering (pp. 107-118).

[57] Brown, S., 2000. Overview of IEC 61508. Design of electrical/electronic/programmable electronic safety-related systems. Computing & Control Engineering Journal, 11(1), pp.6-12.

[58] CAUFFRIEZ, L., A review of SIL theory and a demonstration on the need to truncate the exponential distribution for the generation of SIS failures.

[59] Gabriel, A., Ozansoy, C. and Shi, J., 2018. Developments in SIL determination and calculation. Reliability Engineering & System Safety, 177, pp.148-161.

[60] Lala, J.H. and Harper, R.E., 1994. Architectural principles for safety-critical real-time applications. Proceedings of the IEEE, 82(1), pp.25-40.

[61] Larson, B.R., Jones, P., Zhang, Y. and Hatcliff, J., 2017. Principles and benefits of explicitly designed medical device safety architecture. Biomedical instrumentation & technology, 51(5), pp.380-389.

[62] Antoine, B., 2013. Systems Theoretic Hazard Analysis (STPA) applied to the risk review of complex systems: an example from the medical device industry (Doctoral dissertation, Massachusetts Institute of Technology).

[63] Hasanain, B., Boyd, A.D., Edworthy, J. and Bolton, M.L., 2017. A formal approach to discovering simultaneous additive masking between auditory medical alarms. Applied Ergonomics, 58, pp.500-514.

[64] Pondy, S.V., Gavaskar, S. and Sumithra, A., A Literature Survey on Improving Fault Tolerance of Software Applications.

[65] Hua, Y., Gang, C., Hongwei, L. and Xiaozong, Y., 2006. Redundant multithreading architecture overview. Wuhan University Journal of Natural Sciences, 11(6), pp.1793-1796.

[66] Maxion, R.A., Siewiorek, D.P. and Elkind, S.A., 1987. Techniques and architectures for fault-tolerant computing. Annual Review of Computer Science, 2(1), pp.469-520.

[67] Strigini, L., 1994. Considerations on current research issues in software safety. Reliability Engineering & System Safety, 43(2), pp.177-188.

[68] Littlewood, B., Popov, P. and Strigini, L., 2001. Modeling software design diversity: a review. ACM Computing Surveys (CSUR), 33(2), pp.177-208.

[69] Tashjian, S.M., Zbozinek, T.D. and Mobbs, D., 2021. A Decision Architecture for Safety Computations. Trends in Cognitive Sciences.

[70] Bonafide, C.P., Zander, M., Graham, C.S., Weirich Paine, C.M., Rock, W., Rich, A., Roberts, K.E., Fortino, M., Nadkarni, V.M., Lin, R. and Keren, R., 2014. Video methods for evaluating physiologic monitor alarms and alarm responses. Biomedical instrumentation & technology, 48(3), pp.220-230.

[71] McCaffery, F., Lepmets, M. and Clarke, P., 2015. Medical device software as a subsystem of an overall medical device.

[72] Dhillon, B.S., 2012. Safety and human error in engineering systems. CRC Press.

[73] World Health Organization, 2010. Medical devices: managing the mismatch: an outcome of the priority medical devices project. World Health Organization.

[74] Shah, J.S. and Maisel, W.H., 2006. Recalls and safety alerts affecting automated external defibrillators. JAMA, 296(6), pp.655-660.

[75] World Health Organization, 2008. World Alliance for Patient Safety. WHO guidelines for safe surgery. http://www. gawande. com/documents/WHOGuidelinesforSafeSurgery. pdf.

[76] Essamé, D., Arlat, J. and Powell, D., 1997, October. Available fail-safe systems. In Proceedings of the Sixth IEEE Computer Society Workshop on Future Trends of Distributed Computing Systems (pp. 176-182). IEEE.

[77] Nicolaidis, M., Noraz, S. and Courtois, B., 1989, January. A generalized theory of fail-safe systems. In 1989 The Nineteenth International Symposium on Fault-Tolerant Computing. Digest of Papers (pp. 398-399). IEEE Computer Society.

[78] Mansoor Baig, M., Gholamhosseini, H., Linden, M. and J Connolly, M., 2014. Review of Vital Signs Monitoring Systems–Patient's Acceptability, Issues and Challenges. Neuroscience and Biomedical Engineering (Discontinued), 2(1), pp.2-13.

[79] Serhani, M.A., T El Kassabi, H., Ismail, H. and Nujum Navaz, A., 2020. ECG monitoring systems: Review, architecture, processes, and key challenges. Sensors, 20(6), p.1796.

[80] Chishti, A. and Walker, I.A., 2019. Patient monitoring techniques. Surgery (Oxford), 37(8), pp.450-459.

[81] Hokstad, P. and Rausand, M., 2008. Common cause failure modeling: status and trends. Handbook of performability engineering, pp.621-640.

[82] Sawyer, D., Aziz, K.J., Backinger, C.L., Beers, E.T., Lowery, A. and Sykes, S.M., 1996. An introduction to human factors in medical devices. US Department of Health and Human Services, Public Health Service, Food and Drug Administration, Center for Devices and Radiological Health.

[83] Matrosova, A., Ostanin, S., Kirienko, I. and Nikolaeva, E., 2015, September. Fault-tolerant high performance scheme design. In 2015 IEEE East-West Design & Test Symposium (EWDTS) (pp. 1-4). IEEE.

[84] Magrabi, F., Aarts, J., Nohr, C., Baker, M., Harrison, S., Pelayo, S., Talmon, J., Sittig, D.F. and Coiera, E., 2013. A comparative review of patient safety initiatives for national health information technology. International journal of medical informatics, 82(5), pp.e139-e148.

[85] Fowler, K., 2004. Mission-critical and safety-critical development. IEEE Instrumentation & Measurement Magazine, 7(4), pp.52-59.

[86] Rafter, N., Hickey, A., Condell, S., Conroy, R., O'Connor, P., Vaughan, D. and Williams, D., 2015. Adverse events in healthcare: learning from mistakes. QJM: An International Journal of Medicine, 108(4), pp.273-277.

[87] Li, X., Huang, M.C., Shen, K. and Chu, L., 2010, June. A realistic evaluation of memory hardware errors and software system susceptibility. In Proc. USENIX Annual Technical Conference (ATC'10) (pp. 75-88).

[88] Loncar-Turukalo, T., Zdravevski, E., da Silva, J.M., Chouvarda, I. and Trajkovik, V., 2019. Literature on wearable technology for connected health: scoping review of research trends, advances, and barriers. Journal of medical Internet research, 21(9), p.e14017.

[89] Borel, J.C., Palot, A. and Patout, M., 2019. Technological advances in home non- invasive ventilation monitoring: reliability of data and effect on patient outcomes. Respirology, 24(12), pp.1143-1151.

[90] kamal Kaur, R., Pandey, B. and Singh, L.K., 2018. Dependability analysis of safety critical systems: Issues and challenges. Annals of Nuclear Energy, 120, pp.127-154.

[91] Thomas, M., 1989, September. Asking for the impossible: The state of the art in safety-related systems. In European Software Engineering Conference (pp. 42-47). Springer, Berlin, Heidelberg.

[92] Ojdanic, M., 2019. Systematic literature review of safety-related challenges for autonomous systems in safety-critical applications.

[93] Kovačević, Ž., Pokvić, L.G., Spahić, L. and Badnjević, A., 2020. Prediction of medical device performance using machine learning techniques: infant incubator case study. Health and Technology, 10(1), pp.151-155.

[94] Çoban, S., Gökalp, M.O., Gökalp, E., Eren, P.E. and Koçyiğit, A., 2018, November. [WiP] Predictive maintenance in healthcare services with big data technologies. In 2018 IEEE 11th Conference on Service-Oriented Computing and Applications (SOCA) (pp. 93-98). IEEE.

[95] Maktoubian, J. and Ansari, K., 2019. An IoT architecture for preventive maintenance of medical devices in healthcare organizations. Health and Technology, 9(3), pp.233-243.

[96] Angehrn, Z., Haldna, L., Zandvliet, A.S., Gil Berglund, E., Zeeuw, J., Amzal, B., Cheung, S.Y., Polasek, T.M., Pfister, M., Kerbusch, T. and Heckman, N.M., 2020. Artificial intelligence and machine learning applied at the point of care. Frontiers in Pharmacology, 11, p.759.

[97] Davidson, P.M., Newton, P.J., Tankumpuan, T., Paull, G. and Dennison-Himmelfarb, C., 2015. Multidisciplinary management of chronic heart failure: principles and future trends. Clinical Therapeutics, 37(10), pp.2225-2233.

[98] Hudson, L.D., 1985. Design of the intensive care unit from a monitoring point of view. Respiratory care, 30(7), pp.549-559.

[99] Birsch, D., 2004. Moral responsibility for harm caused by computer system failures. Ethics and Information Technology, 6(4), pp.233-245.

[100] This section has been adapted, with permission, from Glaeser D.H., Thomas L.J. Jr. (1975). Computer monitoring in patient care. Annual Review of Biophysics and Bioengineering, 4:449–476, copyright Annual Reviews, Inc.

[101]Pelech, A.N., 2004. The physiology of cardiac auscultation. Pediatric Clinics, 51(6), pp.1515-1535.

[102]Li, S., Li, F., Tang, S. and Xiong, W., 2020. A review of computer-aided heart sound detection techniques. BioMed research international, 2020.

[103]Luo, R.C. and Kay, M.G., 1989. Multisensor integration and fusion in intelligent systems. IEEE Transactions on Systems, Man, and Cybernetics, 19(5), pp.901-931.

[104]Sha, L., Gopalakrishnan, S., Liu, X. and Wang, Q., 2008, June. Cyber-physical systems: A new frontier. In 2008 IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing (sutc 2008) (pp. 1-9). IEEE.

[105]Yu, X. and Jiang, J., 2015. A survey of fault-tolerant controllers based on safety-related issues. Annual Reviews in Control, 39, pp.46-57.

[106]Siewiorek, D.P., 1991. Architecture of fault-tolerant computers: An historical perspective. Proceedings of the IEEE, 79(12), pp.1710-1734.

[107]Khraisha, R., An Overview of Different TMR Design Techniques with Comparison to Alternative Fault-Tolerant Design Methods for FPGAs. Memory, 13, pp.74-6.

[108]Raghunath, B.H. and Aravind, H.S., 2017. Fault Tolerant Techniques for FPGAs: A Review.

[109]Miclăuş, T., Valla, V., Koukoura, A., Nielsen, A.A., Dahlerup, B., Tsianos, G.I. and Vassiliadis, E., 2020. Impact of Design on Medical Device Safety. Therapeutic Innovation & Regulatory Science, 54(4), pp.839-849.

[110]Abid, A., Khan, M.T. and Iqbal, J., 2021. A review on fault detection and diagnosis techniques: basics and beyond. Artificial Intelligence Review, 54(5), pp.3639-3664.

[111]Panescu, D., 2009, September. Medical device development. In 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (pp. 5591-5594). IEEE.

[112]Radu, L.D., 2020. Disruptive technologies in smart cities: A survey on current trends and challenges. Smart Cities, 3(3), pp.1022-1038.

[113]"Medical Device Databases," US Food and Drug Administration, 28 Mar.2019; www.fda.gov/MedicalDevices/DeviceRegulationandGuid ance/Databases/default.htm.

[114]Wallace, D.R. and Kuhn, D.R., 2001. Failure modes in medical device software: an analysis of 15 years of recall data. International Journal of Reliability, Quality and Safety Engineering, 8(04), pp.351-371.

[115]Thirumalai, S. and Sinha, K.K., 2011. Product recalls in the medical device industry: An empirical exploration of the sources and financial consequences. Management Science, 57(2), pp.376-392.

[116]Bliznakov, Z., Mitalas, G. and Pallikarakis, N., 2007. Analysis and classification of medical device recalls. In World congress on medical physics and biomedical engineering 2006 (pp. 3782-3785). Springer, Berlin, Heidelberg

[117]Simone, L.K., 2013. Software-related recalls: an analysis of records. Biomedical instrumentation & technology, 47(6), pp.514-522. https://doi.org/10.2345/0899-8205-47.6.514

[118]Hravnak, M., Pellathy, T., Chen, L., Dubrawski, A., Wertz, A., Clermont, G. and Pinsky, M.R., 2018. A call to alarms: Current state and future directions in the battle against alarm fatigue. Journal of electrocardiology.

[119]Tscholl, D.W., Handschin, L., Rössler, J., Weiss, M., Spahn, D.R. and Nöthiger, C.B., 2019. It's not you, it's the design-common problems with patient monitoring reported by anesthesiologists: a mixed qualitative and quantitative study. BMC anesthesiology, 19(1), pp.1-10.

[120]Chung, W.K., 1988. A k-out-of-N: G redundant system with dependent failure rates and common-cause failures. Microelectronics Reliability, 28(2), pp.201-203.

[121]Bequette, B.W., 2014. Fault detection and safety in closed-loop artificial pancreas systems. Journal of diabetes science and technology, 8(6), pp.1204-1214.

[122]Torres-Pomales, W., 2000. Software fault tolerance: A tutorial.

[123]Kuhn, D.R., Wallace, D.R. and Gallo, A.M., 2004. Software fault interactions and implications for software testing. IEEE transactions on software engineering, 30(6), pp.418-421.

[124]Goodman, G.R., 2002. Medical device error. Critical Care Nursing Clinics, 14(4), pp.407-416.

[125]Bensink, M., Hailey, D. and Wootton, R., 2006. A systematic review of successes and failures in home telehealth: preliminary results. Journal of telemedicine and telecare, 12(3_suppl), pp.8-16.

[126]Stadler, J.J. and Seidl, N.J., 2013, January. Software failure modes and effects analysis. In 2013 Proceedings Annual Reliability and Maintainability Symposium (RAMS) (pp. 1-5). IEEE.

[127]Hildrew, D.M. and Molony, T.B., 2013. Nucleus N5 CI500 series implant recall: hard failure rate at a major Cochlear implantation center. The Laryngoscope, 123(11), pp.2829-2833.

[128]Castano, V. and Schagaev, I., 2015. Dealing with faults: Redundancy. Resilient computer system design, pp.39-78.

[129]Edworthy, J.R., McNeer, R.R., Bennett, C.L., Dudaryk, R., McDougall, S.J., Schlesinger, J.J., Bolton, M.L., Edworthy, J.D.R., Özcan, E., Boyd, A.D. and Reid, S.K., 2018. Getting Better Hospital Alarm Sounds Into a Global Standard. Ergonomics in Design, 26(4), pp.4-13.

[130]Bach, T.A., Berglund, L.M. and Turk, E., 2018. Managing alarm systems for quality and safety in the hospital setting. BMJ Open Qual, 7(3), p.e000202.

[131]Hrgarek, N., 2012, June. Certification and regulatory challenges in medical device software development. In 2012 4th International Workshop on Software Engineering in Health Care (SEHC) (pp. 40-43). IEEE.

[132]Bovee, M.W., Paul, D.L. and Nelson, K.M., 2001. A framework for assessing the use of third-party software quality assurance standards to meet FDA medical device software process control guideline's. IEEE Transactions on Engineering Management, 48(4), pp.465-478.

[133]Sheng, H., Schwarz, M. and Borcsok, J., 2013, October. Modeling a safety-related system for continuous non-invasive blood pressure monitoring. In Biomedical Circuits and Systems Conference (BioCAS), 2013 IEEE (pp. 254-257). IEEE.

[134]Alemzadeh, H., Di Martino, C., Jin, Z., Kalbarczyk, Z.T. and Iyer, R.K., 2012, June. Towards resiliency in embedded medical monitoring devices. In Dependable Systems and Networks Workshops (DSN-W), 2012 IEEE/IFIP 42nd International Conference on (pp. 1-6). IEEE.

[135]Börcsök, J., 2004. Electronic safety systems: hardware concepts, models, and calculations. Hüthig.

[136]Vescio, B., Salsone, M., Gambardella, A. and Quattrone, A., 2018. Comparison between Electrocardiographic and Earlobe Pulse Photoplethysmographic Detection for Evaluating Heart Rate Variability in Healthy Subjects in Short-and Long-Term Recordings. Sensors, 18(3), p.844.

[137]Hsiao, C.C., Horng, J., Lee, R.G. and Lin, R., 2017, October. Design and implementation of auscultation blood pressure measurement using vascular transit time and physiological parameters. In Systems, Man, and Cybernetics (SMC), 2017 IEEE International Conference on (pp. 2996-3001). IEEE.

[138]Miao, F., Fu, N., Zhang, Y.T., Ding, X.R., Hong, X., He, Q. and Li, Y., 2017. A novel continuous blood pressure estimation approach based on data mining techniques. IEEE J. Biomed. Health Inform, 21, pp.1730-1740.

[139]Selvaraj, N., Jaryal, A., Santhosh, J., Deepak, K.K. and Anand, S., 2008. Assessment of heart rate variability derived from finger-tip photoplethysmography as compared to electrocardiography. Journal of medical engineering & technology, 32(6), pp.479-484.

[140]I. Tumer and C. Smidts, "Integrated Design-Stage Failure Analysis of Software-Driven Hardware Systems," in IEEE Transactions on Computers, vol. 60, no. 8, pp. 1072-1084, Aug. 2011. doi: 10.1109/TC.2010.245

[141]Larson, B., Hatcliff, J., Fowler, K. and Delange, J., 2013. Illustrating the AADL error modeling annex (v. 2) using a simple safety-critical medical device. ACM SIGAda Ada Letters, 33(3), pp.65-84.

[142]S. Hussain, M. Mokhtar and J. M. Howe, "Sensor Failure Detection, Identification, and Accommodation Using Fully Connected Cascade Neural Network," in IEEE Transactions on Industrial Electronics, vol. 62, no. 3, pp. 1683-1692, March 2015.

[143]C. J. Lee, S. M. Baek and S. J. Lee, "Setpoint Methodology Improvement Considering Beyond Design Basis Events for Safety-Related Instrumentation," in IEEE Transactions on Nuclear Science, vol. 61, no. 4, pp. 2120-2130, Aug. 2014.

[144]Y. Li et al., "Feedback-Based Low-Power Soft-Error-Tolerant Design for Dual-Modular Redundancy," in IEEE Transactions on Very Large Scale Integration (VLSI) Systems, vol. 26, no. 8, pp. 1585-1589, Aug. 2018.

[145]Y. Kimura, K. H. Hasegawa and A. Sekiguchi, "Microprocessor-Based System for Processing Redundant Instrumentation Signals," in IEEE Transactions on Industrial Electronics and Control Instrumentation, vol. IECI-27, no. 3, pp. 218-222, Aug. 1980.

[146]Elakeili, S., 2015. Fail-safe test generation of safety critical systems (Doctoral dissertation, University of Denver).

[147]Abdali-Mohammadi, F., Bajalan, V., & Fathi, A. (2015). Toward a Fault Tolerant Architecture for Vital Medical-Based Wearable Computing. Journal of Medical Systems, 39(12). doi:10.1007/s10916-015-0347-7

[148]Brazil, P.G., A Review of Fault Tolerability in Triple Modular Redundancy Schemes.

[149]U. Afzaal and J. Lee, "A Self-Checking TMR Voter for Increased Reliability Consensus Voting in FPGAs," in IEEE Transactions on Nuclear Science, vol. 65, no. 5, pp. 1133-1139, May 2018.

[150]I. B. M. Matsuo, L. Zhao and W. Lee, "A Dual Modular Redundancy Scheme for CPU–FPGA Platform-Based Systems," in IEEE Transactions on Industry Applications, vol. 54, no. 6, pp. 5621-5629, Nov.-Dec. 2018.

[151]P. Varley, "Techniques for development of safety-related software for surgical robots," in IEEE Transactions on Information Technology in Biomedicine, vol. 3, no. 4, pp. 261-267, Dec. 1999.

[152]S. Lee, Y. Yamada, K. Ichikawa, O. Matsumoto, K. Homma and E. Ono, "Safety-Function Design for the Control System of a Human-Cooperative Robot Based on Functional Safety of Hardware and Software," in IEEE/ASME Transactions on Mechatronics, vol. 19, no. 2, pp. 719-729, April 2014.

[153]Jetley, R., Iyer, S.P. and Jones, P., 2006. A formal methods approach to medical device review. Computer, 39(4), pp.61-67.

[154]Lin, Q.L., Wang, D.J., Lin, W.G. and Liu, H.C., 2014. Human reliability assessment for medical devices based on failure mode and effects analysis and fuzzy linguistic theory. Safety science, 62, pp.248-256.

[155]Onofrio, R., Piccagli, F. and Segato, F., 2015. Failure Mode, Effects and Criticality Analysis (FMECA) for medical devices: Does standardization foster improvements in the practice?. Procedia Manufacturing, 3, pp.43-50.

[156]Bouti, A. and Kadi, D.A., 1994. A state-of-the-art review of FMEA/FMECA. International Journal of reliability, quality and safety engineering, 1(04), pp.515-543.

[157]Hyman, W.A. and Johnson, E., 2008. Fault tree analysis of clinical alarms. Journal of Clinical Engineering, 33(2), pp.85-94.

[158]Goel, L.R., Gupta, R. and Agnihotri, R.K., 1989. Analysis of a three-unit redundant system with two types of repair and inspection. Microelectronics Reliability, 29(5), pp.769-773.

[159]Notash, L. and Huang, L., 2003. On the design of fault tolerant parallel manipulators. Mechanism and Machine Theory, 38(1), pp.85-101.

[160]Amari, S.V., Pham, H. and Misra, R.B., 2012. Reliability characteristics of $ k $-out-of-$ n $ warm standby systems. IEEE Transactions on Reliability, 61(4), pp.1007-1018.

[161]Xing, L., Tannous, O. and Dugan, J.B., 2011. Reliability analysis of nonrepairable cold-standby systems using sequential binary decision diagrams. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 42(3), pp.715-726.

[162]Levitin, G., Xing, L. and Dai, Y., 2013. Optimal sequencing of warm standby elements. Computers & Industrial Engineering, 65(4), pp.570-576.

[163]Tannous, O., Xing, L., Rui, P., Xie, M. and Ng, S.H., 2011, December. Redundancy allocation for series-parallel warm-standby systems. In 2011 IEEE International Conference on Industrial Engineering and Engineering Management (pp. 1261-1265). IEEE.

[164]Zhang, T., Xie, M. and Horigome, M., 2006. Availability and reliability of k-out-of-(M+ N): G warm standby systems. Reliability Engineering & System Safety, 91(4), pp.381-387.

[165]Wu, X., Hillston, J. and Feng, C., 2016. Availability Modeling of Generalized $ k $-Out-of-$ n $: G Warm Standby Systems With PEPA. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 47(12), pp.3177-3188.

[166]Zhai, Q., Peng, R., Xing, L. and Yang, J., 2013. Binary decision diagram-based reliability evaluation of k-out-of-(n+ k) warm standby systems subject to fault-level coverage. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 227(5), pp.540-548.

[167]Eryilmaz, S., 2013. Reliability of a k-out-of-n system equipped with a single warm standby component. IEEE Transactions on Reliability, 62(2), pp.499-503.

[168]Mani, D. and Mahendran, A., 2017. Availability modelling of fault tolerant cloud computing system. Int. J. Intell. Eng. Syst, 10(1), pp.154-165.

[169]Rozewski, C., Tendick, M. and Neenah, W.I., Design for high reliability–meeting the goals of high yield and reduced field failures during the medical product development process.

[170]Lee, I., Pappas, G.J., Cleaveland, R., Hatcliff, J., Krogh, B.H., Lee, P., Rubin, H. and Sha, L., 2006. High-confidence medical device software and systems. Computer, 39(4), pp.33-38.

[171]Grottke, M., Sun, H., Fricks, R.M. and Trivedi, K.S., 2008, May. Ten fallacies of availability and reliability analysis. In International Service Availability Symposium (pp. 187-206). Springer, Berlin, Heidelberg.

[172]Jain, M. and Gupta, R., 2011. Redundancy issues in software and hardware systems: an overview. International Journal of Reliability, Quality and Safety Engineering, 18(01), pp.61-98.

[173]Zhu, Y.M., 2017. Failure-Modes-Based Software Reading. In Failure-Modes-Based Software Reading (pp. 29-37). Springer, Cham.

[174]Zidi, S., Moulahi, T. and Alaya, B., 2017. Fault detection in wireless sensor networks through SVM classifier. IEEE Sensors Journal, 18(1), pp.340-347.

[175]Neumann, P.G., Goldberg, J., Levitt, K.N. and Wensley, J.H., 1973. A Study of Fault-Tolerant Computing. STANFORD RESEARCH INST MENLO PARK CA.

[176]Barabady, J., 2005. Improvement of system availability using reliability and maintainability analysis (Doctoral dissertation, Luleå tekniska universitet).

[177]Koren, I. and Krishna, C.M., 2020. Fault-tolerant systems. Morgan Kaufmann.

[178]Anagnostaki, A.P., Pavlopoulos, S., Kyriakou, E. and Koutsouris, D., 2002. A novel codification scheme based on the" VITAL" and" DICOM" standards for telemedicine applications. IEEE Transactions on Biomedical Engineering, 49(12), pp.1399-1411.

[179]Santini, M., Brachmann, J., Cappato, R., Davies, W., Farrè, J., Levy, S., Quesada, A., Ricci, R.P., Rowland, E. and Sulke, N., 2006. Recommendations of the European Cardiac Arrhythmia Society Committee on device failures and complications. Pacing and clinical electrophysiology, 29(6), pp.653-669.

[180]International Electrotechnical Commission, 1998. IEC 61508 Functional safety of electrical/electronic/programmable electronic safety-related systems. International Electrotechnical Commission, Geneva, Switzerland.

[181]DeHon, A., 2008. Defect and fault tolerance. Reconfigurable Computing, pp.829-852.

[182]Albano, M., Ferreira, L.L., Di Orio, G., Maló, P., Webers, G., Jantunen, E., Gabilondo, I., Viguera, M., Papa, G. and Novak, F., 2018, April. Sensors: the enablers for proactive maintenance in the real world. In 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 569-574). IEEE.

[183]Brixey, J., Johnson, T.R. and Zhang, J., 2002. Evaluating a medical error taxonomy. In Proceedings of the AMIA Symposium (p. 71). American Medical Informatics Association.

[184]Gia, T.N., Rahmani, A.M., Westerlund, T., Liljeberg, P. and Tenhunen, H., 2015, April. Fault tolerant and scalable IoT-based architecture for health monitoring. In 2015 IEEE Sensors Applications Symposium (SAS) (pp. 1-6). IEEE.

[185]Su, S.Y. and Spillman, R.J., 1977, June. An overview of fault-tolerant digital system architecture. In Proceedings of the June 13-16, 1977, national computer conference (pp. 19-26).

[186]Stamatis, D.H., 2014. Introduction to risk and failures: tools and methodologies. CRC Press.

[187]Miclăuş, T., Valla, V., Koukoura, A., Nielsen, A.A., Dahlerup, B., Tsianos, G.I. and Vassiliadis, E., 2020. Impact of Design on Medical Device Safety. Therapeutic Innovation & Regulatory Science, 54(4), pp.839-849.

[188]DeMarco, C.T., 2011. Medical device design and regulation. Quality Press.

[189]Edition, F., 1996. Medical device quality systems manual: a small entity compliance guide.

[190]Hegde, V. and Raheja, D., 2010, January. Design for reliability in medical devices. In 2010 Proceedings-Annual Reliability and Maintainability Symposium (RAMS) (pp. 1-6). IEEE.

[191]Gheraibia, Y., Kabir, S., Aslansefat, K., Sorokos, I. and Papadopoulos, Y., 2019. Safety+ AI: A Novel Approach to Update Safety Models Using Artificial Intelligence. IEEE Access, 7, pp.135855-135869.

[192]Alemzadeh, H., Di Martino, C., Jin, Z., Kalbarczyk, Z.T. and Iyer, R.K., 2012, June. Towards resiliency in embedded medical monitoring devices. In IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN 2012) (pp. 1-6). IEEE.

[193]Essame, D., Arlat, J. and Powell, D., 1997, October. Available fail-safe systems. In Proceedings of the Sixth IEEE Computer Society Workshop on Future Trends of Distributed Computing Systems (pp. 176-182). IEEE.

[194]Sinex, J.E., 1999. Pulse oximetry: principles and limitations. The American journal of emergency medicine, 17(1), pp.59-66.

[195]Pinto, J.R., Cardoso, J.S. and Lourenço, A., 2018. Evolution, current challenges, and future possibilities in ECG biometrics. IEEE Access, 6, pp.34746-34776.

[196]Zhang, Q., Zeng, X., Hu, W. and Zhou, D., 2017. A machine learning-empowered system for long-term motion-tolerant wearable monitoring of blood pressure and heart rate with ear-ECG/PPG. IEEE Access, 5, pp.10547-10561.

[197]Avram, R., Tison, G.H., Aschbacher, K. et al. Real-world heart rate norms in the Health eHeart study. npj Digit. Med. 2, 58 (2019) doi:10.1038/s41746-019-0134-9

[198]Li, J., Deng, G., Wei, W., Wang, H. and Ming, Z., 2016. Design of a real-time ECG filter for portable mobile medical systems. IEEE Access, 5, pp.696-704.

[199]Cobus, V. and Heuten, W., 2019. To Beep or Not to Beep? Evaluating Modalities for Multimodal ICU Alarms. Multimodal Technologies and Interaction, 3(1), p.15.

[200]Prasada Raju L., Anumukonda M. and Roy Chowdhury S. (2019). Safety-related Studies on Non-Invasive Biomedical Signals and Its Aptness Usage in Design of Fault Tolerant Multimodal Human Health Monitoring System. In Doctoral Consortium - Volume 1: DCBIOSTEC, ISBN, pages 3-14

[201]Elamaran, V., Arunkumar, N., Hussein, A.F., Solarte, M. and Ramirez-Gonzalez, G., 2018. Spectral fault recovery analysis revisited with Normal and abnormal heart sound signals. IEEE Access, 6, pp.62874-62879.

[202]Xiao, F., 2018. A hybrid fuzzy soft sets decision making method in medical diagnosis. IEEE Access, 6, pp.25300-25312.

[203]A. Riasi and M. Mohebbi, "Prediction of ventricular tachycardia using morphological features of ECG signal," 2015 The International Symposium on Artificial Intelligence and Signal Processing (AISP), Mashhad, 2015, pp. 170-175.

[204]Pan, W., He, A., Feng, K., Li, Y., Wu, D. and Liu, G., 2019. Multi-frequency components entropy as novel heart rate variability indices in congestive heart failure assessment. IEEE Access, 7, pp.37708-37717.

[205]Pang, Z., Yang, G., Khedri, R. and Zhang, Y.T., 2018. Introduction to the special section: convergence of automation technology, biomedical engineering, and health informatics toward the healthcare 4.0. IEEE Reviews in Biomedical Engineering, 11, pp.249-259.

[206]Sidek, K.A., Khalil, I. and Jelinek, H.F., 2014. ECG biometric with abnormal cardiac conditions in remote monitoring system. IEEE Transactions on systems, man, and cybernetics: systems, 44(11), pp.1498-1509.

[207]Paradkar, N.S. and Chowdhury, S.R., 2015. Fuzzy entropy based detection of tachycardia and estimation of pulse rate through fingertip photoplethysmography. Journal of Medical and Bioengineering Vol, 4(1).

[208]Chowdhury, S.R., 2012. Field programmable gate array based fuzzy neural signal processing system for differential diagnosis of QRS complex tachycardia and tachyarrhythmia in noisy ECG signals. Journal of medical systems, 36(2), pp.765-775.

[209]Laible, U., Bürger, T. and Pritschow, G., 2004. A fail-safe dual channel robot control for surgery applications. Safety science, 42(5), pp.423-436.

[210]Z. Li, C. Yang and E. Burdet, "Guest Editorial An Overview of Biomedical Robotics and Bio-Mechatronics Systems and Applications," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 46, no. 7, pp. 869-874, July 2016.

[211]Chun-Chieh, et al. "Design and implementation of auscultation blood pressure measurement using vascular transit time and physiological parameters." Systems, Man, and Cybernetics (SMC), 2017 IEEE International Conference on. IEEE, 2017.

[212]Simone, L.K., 2013. Software-related recalls: an analysis of records. Biomedical instrumentation & technology, 47(6), pp.514-522. https://doi.org/10.2345/0899-8205-47.6.514

[213]Kaushik, R., Desreumaux, P. and Mouret, J.B., 2020. Adaptive prior selection for repertoire-based online adaptation in robotics. Frontiers in Robotics and AI, 6, p.151.

[214]Jin, L., Liao, B., Liu, M., Xiao, L., Guo, D. and Yan, X., 2017. Different-level simultaneous minimization scheme for fault tolerance of redundant manipulator aided with discrete-time recurrent neural network. Frontiers in neurorobotics, 11, p.50.

[215]D. Saxena and V. Raychoudhury, "Design and Verification of an NDN-Based Safety-Critical Application: A Case Study With Smart Healthcare," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 49, no. 5, pp. 991-1005, May 2019.doi:10.1109/TSMC.2017.2723843,URL: http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=7990549&isnumber=8691626

[216]EN, C.S., 2003. 50129-2003 Railway applications: communications, signaling and processing systems—safety related electronic systems for signaling. British Standards Institution (BSI), London.

[217]Bland, J.M. and Altman, D.G., 2010. Statistical methods for assessing agreement between two methods of clinical measurement. International journal of nursing studies, 47(8), pp.931-936.

[218]Myles, P.S. and Cui, J., 2007. I. Using the Bland–Altman method to measure agreement with repeated measures.

[219]Gabriel, A., 2017. Design and evaluation of safety instrumented systems: A simplified and enhanced approach. IEEE Access, 5, pp.3813-3823.

[220]Song, X., Zhai, Z., Lv, R., Guo, Y. and Zhu, P., 2017. Optimal Design of the $ k $-Out-of-$ n $: G (F) Majority Voter. IEEE Access, 5, pp.22647-22656.

[221]P. Lakkamraju, M. Anumukonda and S. R. Chowdhury, "Improvements in Accurate Detection of Cardiac Abnormalities and Prognostic Health Diagnosis Using Artificial Intelligence in Medical Systems," in IEEE Access, vol. 8, pp. 32776-32782, 2020, doi: 10.1109/ACCESS.2020.2965396.

[222]Wikipedia Contributors (2019). Heart rate. [online] Wikipedia. Available at: https://en.wikipedia.org/wiki/Heart_rate.

[223]Kannan, B. and Parker, L.E. (2007). Metrics for quantifying system performance in intelligent, fault-tolerant multi-robot teams. [online] IEEE Xplore. doi:10.1109/IROS.2007.4399530.

[224]Anumukonda, M., Ramasahayam, S., Raju, L.P. and Chowdhury, S.R., 2015, December. Detection of cardio auscultation using MEMS microphone. In 2015 9th International Conference on Sensing Technology (ICST) (pp. 173-177). IEEE.

[225]Wood, R., Belles, R. and Cetiner, M., 2009. Diversity Strategies for NPP I&C Systems. NUREG/CR-7007 ORNL/TM-2009/302.

[226]Cleary, K. and Nguyen, C., 2001. State of the art in surgical robotics: clinical applications and technology challenges. Computer Aided Surgery, 6(6), pp.312-328.

[227]Ikuta, K. and Nokata, M., 1999. General evaluation method of safety for human-care robots. In Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No. 99CH36288C) (Vol. 3, pp. 2065-2072). IEEE.

[228]Ellenby, S.B., 1994, April. Safety issues concerning medical robotics. In IEE Colloquium on Safety and Reliability of Complex Robotic Systems (pp. 3-1). IET.

[229]Alemzadeh, H., Raman, J., Leveson, N. and Iyer, R.K., 2013. Safety implications of robotic surgery: A study of 13 years of FDA data on da Vinci surgical systems. Coordinated Science Laboratory, University of Illinois at Urbana-Champaign.

[230]Zhao, F.J., Zhou, Z.J., Hu, C.H., Chang, L.L., Zhou, Z.G. and Li, G.L., 2018. A new evidential reasoning-based method for online safety assessment of complex systems. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 48(6), pp.954-966.

[231]Fei, B., Ng, W.S., Chauhan, S. and Kwoh, C.K., 2001. The safety issues of medical robotics. Reliability Engineering & System Safety, 73(2), pp.183-192.

[232]Taylor, R.H., 2006. A perspective on medical robotics. Proceedings of the IEEE, 94(9), pp.1652-1664.

[233]Ng, W.S. and Tan, C.K., 1996. On safety enhancements for medical robots. Reliability Engineering & System Safety, 54(1), pp.35-45.

[234]Rovetta, A., 2000. Telerobotic surgery control and safety. In Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065) (Vol. 3, pp. 2895-2900). IEEE.

[235]Korb, W., Kornfeld, M., Birkfellner, W., Boesecke, R., Figl, M., Fuerst, M., Kettenbach, J., Vogler, A., Hassfeld, S. and Kornreif, G., 2005. Risk analysis and safety assessment in surgical robotics: A case study on a biopsy robot. Minimally Invasive Therapy & Allied Technologies, 14(1), pp.23-31.

[236]Lakkamraju, P., Anumukonda, M. and Chowdhury, S.R., 2021. Improvements in Medical System Safety Analytics for Authentic Measure of Vital Signs Using Fault-Tolerant Design Approach. Frontiers in Medical Technology, 3, p.666671.

[237]Anumukonda, M., Lakkamraju, P.R. and Chowdhury, S.R., 2020, January. Classification of Abnormal and Normal Heart Sounds Using the MEMS based High Performance PhonoCardioGraphy System. In 2020 International Conference on Artificial Intelligence and Signal Processing (AISP) (pp. 1-7). IEEE.

[238]Bhattacharya, J. and Kanjilal, P.P., 1999. Assessing determinism of photo-plethysmographic signal. IEEE transactions on systems, man, and cybernetics-part A: systems and humans, 29(4), pp.406-410.

[239]Vermesan, O., Coppola, M., Bahr, R., Bellmann, R.O., Martinsen, J.E., Kristoffersen, A., Hjertaker, T., Breiland, J., Andersen, K., Sand, H.E. and Lindberg, D., 2022. An Intelligent Real-Time Edge Processing Maintenance System for Industrial Manufacturing, Control, and Diagnostic. Frontiers in Chemical Engineering, p.58.

[240]Khan, A.H., Shakeel, S., Hooda, K., Siddiqui, K. and Jafri, L., 2019. Best practices in the implementation of a point of care testing program: experience from a tertiary care hospital in a developing country. EJIFCC, 30(3), p.288.

[241]Darwin, S. and Raj, E.F.I., 2023. A detailed review on embedded based heartbeat monitoring systems. Smart Embedded Systems and Applications, p.79.

[242]Srovnal, V., 2005. Using of embedded systems in biomedical applications. In IFMBE Proc (Vol. 11, No. 1, pp. 1727-1983).

[243]Vasava, D. and Deshpande, S., 2016. Portable device to monitor vital health parameters. IRJET.

[244]Maano, R.C., Narvaez, J.D., CarylenAbbu, L.A.H., Tolentino, L. and Pavon Jr, G.C., Design of a Vital Signs Checking System for School Clinic Services.

[245]Wang K, Kohane I, Bradshaw KL, Fackler J. A real time patient monitoring system on the World Wide Web. Proc AMIA Annu Fall Symp. 1996:729-32. PMID: 8947761; PMCID: PMC2233054.

[246]Barker, Steven J. PhD, MD. “Motion-Resistant” Pulse Oximetry: A Comparison of New and Old Models. Anesthesia & Analgesia 95(4):p 967-972, October 2002. | DOI: 10.1213/00000539-200210000-00033

[247]Gardner, R.M., Clemmer, T.P., Evans, R.S., Mark, R.G. (2014). Patient Monitoring Systems. In: Shortliffe, E., Cimino, J. (eds) Biomedical Informatics. Springer, London. https://doi.org/10.1007/978-1-4471-4474-8_19

[248]Baig, M.M. and Gholamhosseini, H., 2013. Smart health monitoring systems: an overview of design and modeling. Journal of medical systems, 37, pp.1-14.

[249]Borges, G. and Brusamarello, V., 2016. Sensor fusion methods for reducing false alarms in heart rate monitoring. Journal of clinical monitoring and computing, 30, pp.859-867.

[250]Vadrevu, S. and Manikandan, M.S., 2019. Real-time PPG signal quality assessment system for improving battery life and false alarms. IEEE transactions on circuits and systems II: express briefs, 66(11), pp.1910-1914.

[251]Cho, O.M., Kim, H., Lee, Y.W. and Cho, I., 2016. Clinical alarms in intensive care units: Perceived obstacles of alarm management and alarm fatigue in nurses. Healthcare informatics research, 22(1), pp.46-53.

[252]Imhoff, M. and Kuhls, S., 2006. Alarm algorithms in critical care monitoring. Anesthesia & Analgesia, 102(5), pp.1525-1537.

[253]E. Yanar, "Reduction of false arrhythmia alarms on patient monitoring systems in intensive care units by using fuzzy logic algorithms," M.S. - Master of Science, Middle East Technical University, 2018.

[254]Nizami, S., Greenwood, K., Barrowman, N. and Harrold, J., 2015. Performance evaluation of new-generation pulse oximeters in the NICU: observational study. Cardiovascular engineering and technology, 6, pp.383-391.

[255]Chambrin, M. C. (2001). Alarms in the intensive care unit: how can the number of false alarms be reduced? Critical Care, 5 , 184–188. PMID 11511330.

[256]Shortliffe, H.E. and Cimino, J.J., 2014. Biomedical informatics: computer applications in health care and biomedicine. Springer-Verlag London.

List of Publications

Doctoral Conference: [As part of Thesis work]

[1] Prasada Raju, L.; Anumukonda, M. and Roy Chowdhury, S. (2019). Safety-related Studies on Non-Invasive Biomedical Signals and Its Aptness Usage in Design of Fault Tolerant Multimodal Human Health Monitoring System. In **Doctoral Consortium - DCBIOSTEC**, ISBN , pages 3-14

Journals: [As part of Thesis work]

[2] Lakkamraju, P., Anumukonda, M. and Chowdhury, S.R., 2020. Improvements in Accurate Detection of Cardiac Abnormalities and Prognostic Health Diagnosis Using Artificial Intelligence in Medical Systems. **IEEE Access**, 8, pp.32776-32782.

[3] Lakkamraju, P., Anumukonda, M. and Chowdhury, S.R., 2021. Improvements in Medical System Safety Analytics for Authentic Measure of Vital Signs Using Fault-Tolerant Design Approach. **Frontiers in Medical Technology**, p.45.

[4] Lakkamraju, P., Anumukonda, M. and Chowdhury, S.R., 2022. Enhancements in Safety Analytics of a Medical System for Authentic Measure of Vital Signs Using Edge-AI enabled Fault-tolerant Triple Module Redundancy Design Approach. **Frontiers in Medical Technology**. ***[Submitted and Under Review]***

Journals: [Support work – Not part of Thesis work]

[1] Anumukonda, M., **Lakkamraju, P**. and Chowdhury, S.R., 2021. FPGA-Based High-Performance Phonocardiography System for Extraction of Cardiac Sound Components Using Inverse Delayed Neuron Model. **Frontiers in Medical Technology**, p.38.

Conferences: [Support work – Not part of Thesis work]

[2] Anumukonda, M., Ramasahayam, S., **Raju, L.P**. and Chowdhury, S.R., 2015, December. Detection of cardio auscultation using MEMS microphone. In 2015 9th **International Conference on Sensing Technology (ICST) (pp. 173-177). IEEE**.

[3] Anumukonda, M., **Lakkamraju, P.R**. and Chowdhury, S.R., 2020, January. Classification of Abnormal and Normal Heart Sounds Using the MEMS based High Performance PhonoCardioGraphy System. In 2020 International Conference on **Artificial Intelligence and Signal Processing (AISP) (pp. 1-7). IEEE**.

Book chapter: [Support work – Not part of Thesis work]

[1] S. Roy Chowdhury, G. Sharma, Y. Arora, L.V.R. Prasadaraju, M. Anumukonda, S. Ramasahayam, "Smart circuits for signal conditioning of wearable medical sensors", **Chapter-3 in the book titled Wearable Sensors: Application, Design and Implementation**, edited by S.C. Mukhopadhyay and T. Islam, pp. 3.1-3.28, **IoP Publishing**, 2017

List of Patents

[1] L.V.R. Prasadaraju, A. Madhubabu, S. Roy Chowdhury, "Wearable Hemoglobin Monitoring Device", Indian Patent Application No. 201643036895, dated 26-10-2016. FER – Submitted in July'21

[2] L.V.R. Prasadaraju, A. Madhubabu, S. Roy Chowdhury, "Wearable Cardiac Health Monitoring System", Indian Patent Application No. 201641036083, dated 21-10-2016. FER – Submitted in Feb'22

[3] L.V.R. Prasadaraju, A. Madhubabu, S. Roy Chowdhury, "Wearable Fetal Cardiac Health Monitoring System", Indian Patent Application No. 201643042957, dated 16-12-2016. FER – Submitted in Nov'21

Appendix A– CHMS Schematics