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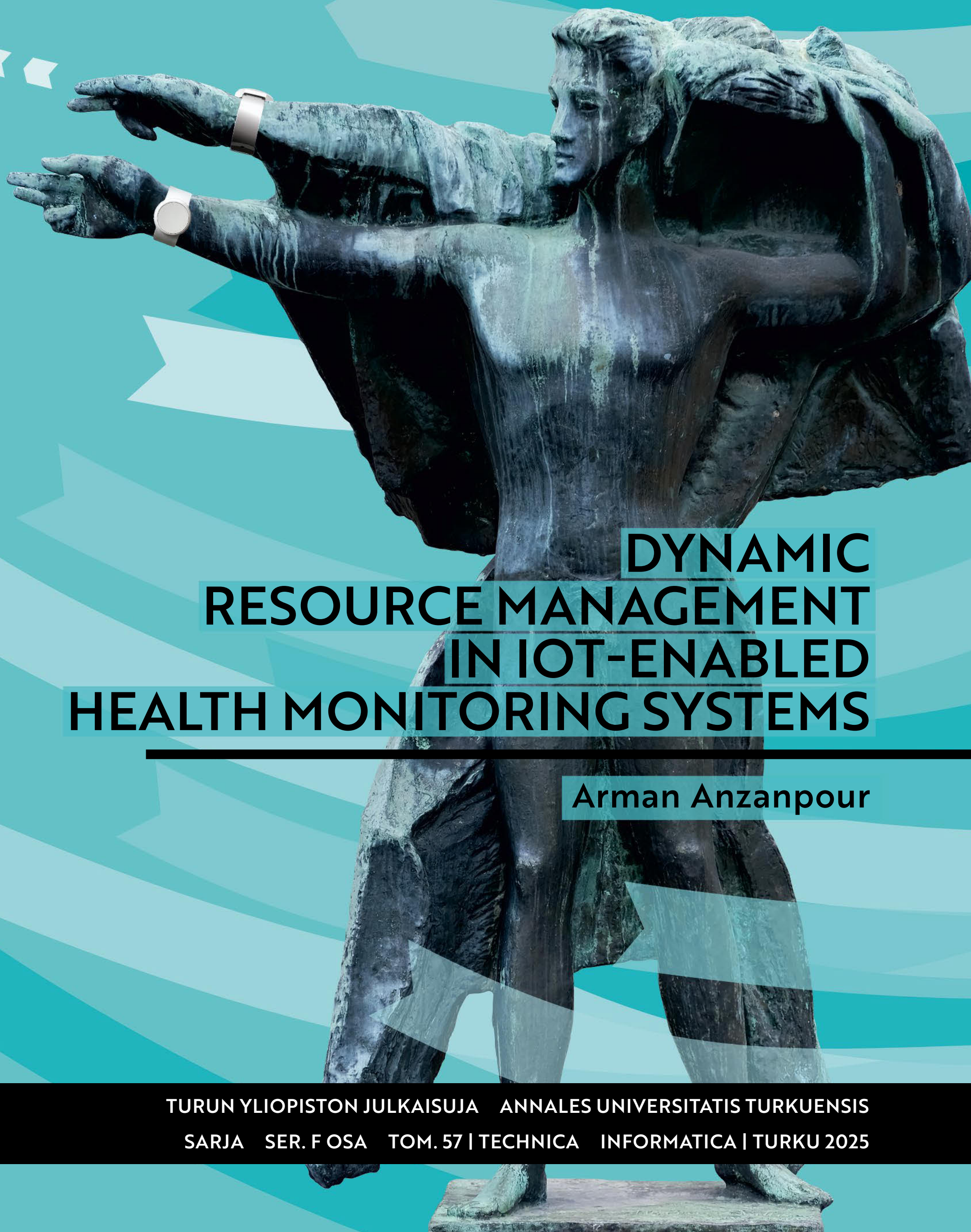

DYNAMIC RESOURCE MANAGEMENT IN IOT-ENABLED HEALTH MONITORING SYSTEMS

Arman Anzanpour

TURUN YLIOPISTON JULKAISUJA ANNALES UNIVERSITATIS TURKUENSIS
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University of Turku

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زما باد برجان آنکس درود
که داد و خرد باشدش تار و پود

فردوسی (۴۰۳-۳۱۹هـ.ش)

We honor those whose core is woven
With justice and wisdom, unbroken

Ferdowsi, Persian poet (940–1025 AD)

This couplet from Ferdowsi's Shahnameh—a book over a millennium old—emphasizes that wisdom and justice are fundamental to human excellence. This ancient insight remarkably parallels modern systems theory, where the deep entanglement of awareness and effective decision-making is recognized as essential for optimal and adaptive functioning.

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ABSTRACT

In recent years, health technologies have become game-changers in addressing healthcare accessibility issues. Despite advancements, quality medical care was not available to everyone for many years due to geographical constraints, limited resources, and high costs. Utilizing remote health services, health technologies are reshaping this situation, offering solutions for universal healthcare access.

This thesis delves into the impact of health technologies, with a focus on IoT-enabled remote health monitoring systems and their potential to revolutionize healthcare delivery. Real-time health assessments and early interventions can be significantly improved by miniaturizing hospital-grade monitoring devices into IoT-based wearables capable of collecting and transmitting biosignals. However, the deployment of IoT-based health monitoring systems faces challenges, mainly related to system resources. The thesis underscores the importance of effective resource management in optimizing these systems where static resource management involves selecting hardware components during design, and dynamic management at runtime ensures adaptability and real-time responsiveness.

Self-awareness enables systems to autonomously monitor, analyze, and adapt their components and behaviors in real-time. Context-awareness allows the system to recognize and respond to environmental and operational contexts, balancing data quality and resource efficiency. Goal management aligns and prioritizes multiple objectives, such as emergency responses, measurement accuracy, and battery optimization, to dynamically allocate resources based on real-time needs. Computation offloading entails redistributing computational tasks across different system layers to maintain performance and timely responses, especially under constrained network conditions.

These methodologies aim to extend hospital-grade early warning systems to home environments, thereby improving the management of chronic conditions and patient outcomes. The strategic resource management approaches ensure that IoT-based health monitoring systems are robust, efficient, and capable of providing continuous, high-quality patient care.

KEYWORDS: Health Technology, Internet of Things (IoT), Remote Health Monitoring, Early Warning Score Systems, Resource Management

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TIIVISTELMÄ

Terveysteknologian kehitys viime vuosina on parantanut terveydenhuollon saavutettavuutta. Tästä positiivisesta kehityksestä huolimatta laadukas terveydenhuolto ei ole maantieteellisten rajoitusten, rajallisten resurssien ja korkeiden kustannusten vuoksi kaikkien saatavilla samalla tavalla. Etäpalveluita hyödyntämällä terveysteknologia on muuttamassa tilannetta ja tarjoaa ratkaisuja terveydenhuollon yleiseen saavutettavuuteen.

Tässä väitöskirjatyössä tarkastellaan digitaalisten ratkaisujen vaikutusta etäterveydenseurantaan, keskittyen erityisesti esineiden internetin avulla toteutettuihin etäterveydenseurannan järjestelmiin ja niiden mahdollisuuksiin parantaa terveydenhuollon saavutettavuutta. Erilaisia terveydenseurannan laitteita voidaan pienentää puettaviksi esineiden internet pohjaisiksi laitteiksi, jotka pystyvät keräämään ja lähettämään käyttäjän biosignaaleja kuten esimerkiksi tietoja sydämen toiminnasta ja happisaturaatiosta. Näiden laitteiden käyttöönotossa on kuitenkin haasteita, jotka liittyvät pääasiassa järjestelmäresursseihin. Väitöskirjassa korostetaan tehokkaan resurssienhallinnan merkitystä näiden järjestelmien optimoinnissa, jossa staattinen resurssienhallinta käsittää laitteistokomponenttien valinnan järjestelmän suunnittelun aikana ja dynaaminen hallinta käytönaikaisen mukauttamisen ja reaaliaikaisen reagointikyvyn optimoinnin muuttuvassa käyttöympäristössä.

Väitöskirjatyössä toteutettu itsetietoisuus mahdollistaa järjestelmän komponenttien ja toiminnan autonomisen valvonnan, analysoinnin ja mukauttamisen reaaliajassa. Kontekstin tunnistaminen, kontekstitietoisuus, mahdollistaa järjestelmän toimintaympäristön ymmärtämisen ja siihen reagoimisen, minkä avulla voidaan tasapainottaa biosignaalien laatua ja resurssitehokkuutta. Tavoitehallinta auttaa asettamaan ja priorisoimaan useita tavoitteita samanaikaisesti– kuten hätätilanteisiin reagointi, mittausten tarkkuus ja akun virrankulutuksen optimointi – ja ohjaamaan resurssien dynaamista allokointia reaaliaikaisen tarpeen mukaan. Järjestelmä hyödyntää myös laskentatehon dynaamista siirtämistä jonka avulla voidaan jakaa laskennallisten tehtävien eri järjestelmätasojen välillä suorituskyvyn ja oikeaikaisen ajoituksen varmistamiseksi.

ASIASANAT: Terveysteknologia, esineiden internet, terveyden etäseuranta, varhaisvaroitusjärjestelmät, resurssienhallinta.

Acknowledgements

I am sincerely grateful to everyone who contributed to this thesis through their guidance or support over the years. My heartfelt thanks go to my supervisors, Prof. Pasi Liljeberg and Prof. Amir M. Rahmani, whose expertise and guidance helped turn my ideas into meaningful research.

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I am thankful to my project supervisor, Tero Koivisto, for giving me the opportunity to apply remote patient monitoring in real-world projects. I learned so much from you and our colleagues, Tuomas Valtonen, Olli Lahdenoja, Ismail Elnaggar, Sepehr Seifizarei, Jonas Sandelin, Yangyang Zhao, Mohammad Feli, and Kianoosh Kazemi, during these collaborations. I also wish to thank Nokia and TES Foundations for supporting this research.

Many thanks to my family and friends in Iran, Finland, and all around the world—your love and encouragement brought joy and balance to my life during this journey. Finally, to my friend, love, and journey companion, Shema—your unwavering support and belief in me were my guiding light. This thesis is as much yours as it is mine.

April 2025
Arman Anzanpour

ARMAN ANZANPOUR

Arman Anzanpour holds a master's degree in Biomedical Engineering from Amirkabir University of Technology in Tehran, Iran. His research is focused on the healthcare Internet of Things, integrating health technology, computer science, and electronic engineering. Arman has authored numerous highly-cited publications and has earned three best paper awards. Additionally, he has received two Research Excellence awards from Nokia and TES foundations for his contributions to the design and development of remote health monitoring systems.

Table of Contents

Abbreviations

AC	Alternating Current
ADC	Analog to Digital Converter
AP	Access Point
API	Application Programming Interface
AVR	Alf and Vegard's RISC processor
BLE	Bluetooth Low Energy
BMI	Body Mass Index
BPM	Beats Per Minute
CCOS	Critical Care Outreach Service
CPR	Cardiopulmonary Resuscitation
CPU	Central Processing Unit
CS	Chip Select (in SPI communication)
DALY	Disability-Adjusted Life Year
DC	Direct Current
DPS	Degrees Per Second
ECG	Electrocardiogram
EEPROM	Electrically Erasable Programmable Read-Only Memory
EWS	Early Warning Score
GPIO	General-Purpose Input/Output
I^2C	Inter-Integrated Circuit
ICU	Intensive Care Unit
IEEE	Institute of Electrical and Electronics Engineers
IMU	Inertial Measurement Unit
I/O	Input / Output
IoT	Internet of Things
IR	Infrared
LDR	Light Dependent Resistor
LED	Light Emitting Diode
LoRa	Long Range
MCU	Microcontroller Unit
MET	Medical Emergency team
MIPS	Million Instructions Per Second
MISO	Master In Slave Out (in SPI communication)

MOSI	Master Out Slave In (in SPI communication)
ODA	Observe, Decide, Act
OECD	The Organization for Economic Co-operation and Development
OIDG	Output-to-Input Data Generation
PAN	Personal Area Network
PART	Patient at Risk Teams
PB	Blood Pressure
PCG	Phonocardiogram
PPG	Photoplethysmography
PWM	Pulse Width Modulation
QoS	Quality of Service
QoE	Quality of Experience
QSPI	Quad Serial Peripheral Interface
RAM	Random Access Memory
RF	Radio Frequency
RH	Relative Humidity
RISC	Reduced Instruction Set Computer
RMSE	Root Mean Square Error
ROM	Read-Only Memory
RR	R-peak to R-peak
RRT	Rapid Response Team
RTC	Real-Time Clock
RX	Receive
SCK	Serial Clock (in SPI communication)
SCL	Serial Clock Line (in I2C communication)
SDA	Serial Data Line (in I2C communication)
SPI	Serial Peripheral Interface
SpO_2	Peripheral Capillary Oxygen Saturation
SRAM	Static Random Access Memory
STA	Station
TCP/IP	Transmission Control Protocol/Internet Protocol
TX	Transmit
UART	Universal Asynchronous Receiver-Transmitter
USART	Universal Synchronous/Asynchronous Receiver-Transmitter
Wi-Fi	Wireless Fidelity
WLAN	Wireless Local Area Network

List of Original Publications

This dissertation is based on the following original publications, which are referred to in the text by their Roman numerals:

Paper I	**Arman Anzanpour**, Delaram Amiri, Iman Azimi, Marco Levorato, Nikil Dutt, Pasi Liljeberg, Amir M. Rahmani, "Edge-Assisted Control for Healthcare Internet-of-Things: A Case Study on PPG-based Early Warning Score", 2020, ACM Transactions on Internet of Things.
Paper II	**Arman Anzanpour**, Humayun Rashid, Amir M. Rahmani, Axel Jantsch, Nikil Dutt, Pasi Liljeberg, "Energy-efficient and Reliable Wearable Internet-of-Things through Fog-Assisted Dynamic Goal Management", 2019, International Conference on Ambient Systems Networks and Technologies, Belgium.
Paper III	**Arman Anzanpour**, Iman Azimi, Maximilian Götzinger, Amir M. Rahmani, Nima TaheriNejad, Pasi Liljeberg, Axel Jantsch, Nikil Dutt, "Self-Awareness in Remote Health Monitoring Systems using Wearable Electronics", 2017, Design, Automation, and Test in Europe Conference, Switzerland.
Paper IV	Axel Jantsch, **Arman Anzanpour**, Hedyeh Kolerdi, Iman Azimi, Lydia Chaido Siafara, Amir M. Rahmani, Nima TaheriNejad, Pasi Liljeberg, Nikil Dutt, "Hierarchical Dynamic Goal Management for IoT Systems", 2018, IEEE International Symposium on Quality Electronic Design, USA.
Paper V	Sina Shahhosseini, **Arman Anzanpour**, Iman Azimi, Sina Labbaf, DongJoo Seo, Sung-Soo Lim, Pasi Liljeberg, Nikil Dutt, and Amir M. Rahmani, "Exploring Computation Offloading in IoT Systems", 2021, Elsevier Journal of Information Systems (InfoSys).

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During the course of doctoral studies, the following peer-reviewed publications were published. Although not included in this thesis, they are closely related to the research presented here.

Paper VI	**Arman Anzanpour**, Amir M. Rahmani, Pasi Liljeberg, Hannu Tenhunen, "Internet of Things Enabled In-Home Health Monitoring System Using Early Warning Score", ACM International Conference on Wireless Mobile Communication and Healthcare, UK, 2015.
Paper VII	**Arman Anzanpour**, Amir M. Rahmani, Pasi Liljeberg, Hannu Tenhunen, "Context-Aware Early Warning System for In-Home Healthcare Using Internet-of-Things", International Conference on IoT Technologies for HealthCare, Springer LNICST, 2015, Italy, 2015.
Paper VIII	Iman Azimi, **Arman Anzanpour**, Amir M. Rahmani, Pasi Liljeberg, Hannu Tenhunen, "Self-Aware Early Warning Score System for IoT-Based Personalized Healthcare", EAI International Conference on IoT and Big Data Technologies for HealthCare, Hungary, 2016.
Paper IX	Iman Azimi, **Arman Anzanpour**, Amir M. Rahmani, Pasi Liljeberg, Tapio Salakoski, "Medical Warning System Based on Internet of Things Using Fog Computing", IEEE International Workshop on Big Data and Information Security, Indonesia, 2016.
Paper X	Mingzhe Jiang, Tuan Nguyen Gia, **Arman Anzanpour**, Amir M. Rahmani, Tomi Westerlund, Sanna Salanterä, Pasi Liljeberg, Hannu Tenhunen, "IoT-based Remote Facial Expression Monitoring System with sEMG Signal", IEEE Sensors Applications Symposium, UK, 2016.
Paper XI	Moreno Ambrosin, **Arman Anzanpour**, Mauro Conti, Tooska Dargahi, Sanaz Rahimi Moosavi, Amir M. Rahmani, Pasi Liljeberg, "On the Feasibility of Attribute-Based Encryption on Internet of Things Devices", IEEE Micro Special Issue on Internet of Things, 2016.

Paper XVIII	Iman Azimi, Janne Takalo-Mattila, **Arman Anzanpour**, Amir M. Rahmani, Juha-Pekka Soininen, Pasi Liljeberg, "Empowering Healthcare IoT Systems with Hierarchical Edge-based Deep Learning", IEEE Workshop on Deep Learning and Edge Computing in IoT-centered Health Applications in conjunction with ACM/IEEE CHASE 2018, USA, 2018.
Paper XIX	Delaram Amiri, **Arman Anzanpour**, Iman Azimi, Marco Levorato, Amir M. Rahmani, Pasi Liljeberg, Nikil Dutt, "Edge-Assisted Sensor Control in Healthcare IoT", IEEE GLOBECOM, UAE, 2018.
Paper XX	Mohammad R. Nakhkash, Tuan Nguyen Gia, Iman Azimi, **Arman Anzanpour**, Amir M. Rahmani, Pasi Liljeberg, "Analysis of Performance and Energy Consumption of Wearable Devices and Mobile Gateways in IoT Applications", International Conference on Omni-layer Intelligent Systems, Greece, 2019.
Paper XXI	Sina Shahosseini, Iman Azimi, **Arman Anzanpour**, Axel Jantsch, Pasi Liljeberg, Nikil Dutt, Amir M. Rahmani, "Dynamic Computation Migration at the Edge: Is There an Optimal Choice?", ACM Great Lakes Symposium on VLSI, 2019.
Paper XXII	Maximilian Götzinger, **Arman Anzanpour**, Iman Azimi, Nima TaheriNejad, Axel Jantsch, Amir M. Rahmani, Pasi Liljeberg, "Confidence-Enhanced Early Warning Score Based on Fuzzy Logic", ACM/Springer Mobile Networks and Applications (ACM/Springer-MONET), 2019.
Paper XXIII	Delaram Amiri, **Arman Anzanpour**, Iman Azimi, Marco Levorato, Pasi Liljeberg, Nikil Dutt, Amir M. Rahmani, "Context-Aware Sensing via Dynamic Programming for Edge-Assisted Wearable Systems", ACM Transactions on Computing for Healthcare (ACM-HEALTH), 2019.
Paper XXIV	Delaram Amiri, **Arman Anzanpour**, Iman Azimi, Amir M. Rahmani, Pasi Liljeberg, Nikil Dutt, Marco Levorato, "Optimizing Energy in Wearable Devices Using Fog Computing", A chapter in Fog Computing: Theory and Practice, Wiley, 2019.

Paper XXV	Mohammad Feli, Iman Azimi, **Arman Anzanpour**, Amir M. Rahmani, Pasi Liljeberg, "An energy-efficient semi-supervised approach for on-device photoplethysmogram signal quality assessment", Smart Health, 2023.

1 Introduction

In harmony with the trend of advancements in science and technology, health technology is making a headway toward modern solutions for healthcare [1]. Health technology, commonly referred to as *health tech*, encompasses a broad range of devices, medicines, procedures, and systems designed to improve healthcare operations and enhance the quality of care. By leveraging faster, easier, and more reliable methods for tracking, diagnosis, and treatment, health tech not only streamlines healthcare systems but also optimizes resources and reduces costs [2]. Among the various facets of health tech, remote health monitoring is experiencing rapid growth. This is largely in response to the limitations in distributing healthcare services within society. Remote health monitoring enables continuous patient care outside traditional clinical settings, addressing accessibility issues and enhancing overall healthcare delivery [3].

1.1 Healthcare Distribution Challenges

For centuries, accessing effective medical treatment has been hindered by several significant challenges. The limited number of medical experts, combined with long distances and restricted transportation options, made healthcare services expensive and inaccessible to the majority of the population. Despite the substantial advancements in medicine, including groundbreaking discoveries and a notable increase in the number of medical professionals, healthcare facilities, and transportation methods, a considerable portion of society still faces barriers to receiving proper medical care [4]. Current data indicates that approximately 4.5 billion people worldwide lacked coverage for essential health services as of 2021, representing 56% of the global population [5; 6; 7]. This marks a decline from 50% in 2017 [6], suggesting we are significantly off track in reaching the sustainable development goal targets for universal health coverage (UHC) by 2030 [7].

Surprisingly, the rebirth of the healthcare distribution challenge is due to the advancements in medical sciences. The discovery of treatments for previously fatal diseases, such as diabetes [8; 9], has led to an increase in life expectancy and a significant rise in the population of elderly individuals struggling with chronic conditions [10; 11]. This demographic shift has outpaced the growth of medical resources, healthcare providers, and logistics, worsening the issue of healthcare accessibility [12; 13]. Numerous efforts have been made over the decades to enhance the accessibility of healthcare services to address this shortfall. The journey began with the utilization of telephone lines and evolved to include internet communications, giving rise to remote health service methods such as telehealth, telemedicine, and remote health monitoring [14; 4]. These innovative approaches not only mitigate healthcare distribution problems but also facilitate preventive care through regular remote check-ups and follow-ups. Today, health technologies have emerged as a promising solution to ensure that everyone in need receives a decent level of care. Leveraging remote health services can bridge the gap in healthcare accessibility and provide quality care to a broader population. This shift toward technology-enabled healthcare can reshape how we deliver and receive medical services, making healthcare more inclusive and accessible for all [15].

As mentioned, the imbalance between available healthcare resources and treatment-seeking individuals is largely attributed to the growing population of elderly people. The cost of medical care can be an indicator of this imbalance. In the United States, as an illustrative example of a global trend, adults aged 65 and older spend healthcare costs over 5 times higher than children and nearly 2.5 times higher than working-age individuals. Despite representing only about 17% of the population, older adults accounted for approximately 37% of all personal healthcare spending. This pattern is not unique to the U.S.; [16] in OECD (The Organization for Economic Co-operation and Development) countries, the over-65 age group typically accounts for 40% to 50% of healthcare spending, with per capita costs three to five times higher than those under 65. These statistics highlight a widespread global phenomenon where aging populations disproportionately impact healthcare expenditures across different societies [17]. As a result, older adults have become the primary target group for receiving remote health services. Since chronic diseases are the most prevalent type of ailments among the elderly, remote monitoring technologies are particularly focused on managing and treating these conditions.

1.2 Chronic Diseases

A chronic condition is a persistent health problem that is either a disease itself or caused by a disease requiring long-term treatment and management. [18] These conditions can be physical, psychological, or cognitive in nature and last for a long time, significantly impacting an individual's daily life activities. Chronic diseases affect daily life by causing functional limitations, restricting an individual's ability to perform everyday tasks and activities. Managing chronic conditions often necessitates using medication or medical devices, tools, and technologies for measurement, adjustment, monitoring, and prevention. Additionally, individuals with chronic diseases may require personal assistance, psychological aid, and ongoing medical and paramedical care. Four major chronic diseases include cardiovascular diseases, cancer, chronic respiratory diseases, and diabetes [19].

In 2019, chronic diseases were responsible for 74% of global deaths and accounted for 63% of global disability-adjusted life-years (DALY). Four major chronic diseases collectively claimed the lives of approximately 33.3 million people in 2019, marking a 28% increase since 2000 [20]. These diseases pose a significant public health challenge in Europe, where they account for 90% of all deaths [21]. In Finland, 60% of all deaths in 2021 were attributed to these four major chronic diseases [22].

Monitoring the health status of chronic patients is crucial, as continuously tracking certain medical parameters can help prevent potential fatalities [23]. Research indicates that most deaths and disabilities among chronic patients occur following a sudden deterioration in their condition. Further studies reveal that preventing such sudden declines can reduce the risk of death or disability by 50% [24; 25]. Importantly, the signs and symptoms of these life-threatening deteriorations can be detected up to 24 hours in advance, making it possible to prevent deaths or irreversible damage [24; 26]. This requires continuous observation for these critical signs and symptoms.

1.3 Medical Early Warning Systems

To discover the early signs and reduce the occurrence of life-threatening deteriorations, several medical Early Warning Score systems (EWS) have been developed and successfully implemented in hospitals over the past few decades [27]. These systems involve recording and comparing vital signs and their trends manually or using electronic measurement devices. However, due to the long-term nature of chronic diseases, most patients live at home, where fatal deteriorations often occur.

In hospital settings, continuous patient monitoring involves measuring biosignals and derived medical parameters to assess a patient's health status. The five vital signs—heart rate, respiration rate, blood oxygen saturation, blood pressure, and body temperature—are the most commonly used parameters. Hospital monitoring prioritizes reliability and accuracy, and there are no constraints on device size or power consumption. As a result, monitoring devices are designed as large units with clearly visible displays, and they rely on permanent wires for power supply and analog or digital signal transmission. To enable chronic patients at home to benefit from the same Early Warning Score methods used in hospitals, the hospital-sized monitoring devices must be miniaturized into wearable devices that are battery-powered and communicate wirelessly. These devices should be lightweight enough for patients to wear continuously, easy to put on and take off, washable or waterproof, and made from biocompatible materials. These

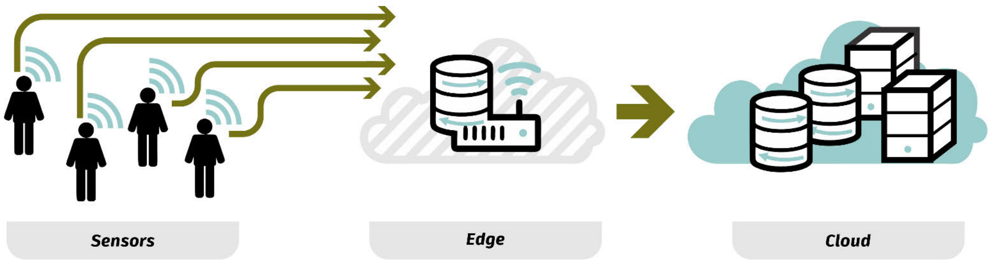

Figure 1. The layered architecture of Internet of Things based health monitoring system.

requirements have challenged continuous patient home monitoring for years.

1.4 Internet of Things Solution

Advancements in the Internet of Things (IoT) [28] have paved the way for a promising future in remote patient monitoring [29]. An IoT framework enables the development of a remote monitoring system that takes advantage of the compact size of sensors and the substantial storage and processing capabilities of cloud servers, operating continuously [30]. This technology has the potential to transform the delivery of medical services, making it possible for chronic patients to receive effective care from the comfort of their own homes [31]. By leveraging IoT, healthcare providers can extend the reach of Early Warning Score methods beyond hospital walls, ensuring that patients receive timely interventions and improving their overall quality of life.

As illustrated in figure 1, an IoT-based health monitoring system consists of three semantic layers. In the sensor layer, a set of sensors collect biosignals; in the edge layer, a gateway device (e.g., a hub or smartphone) receives the collected biosignals via a short-range wireless communication method and passes them to a cloud server through a wired or wireless network. There are unique features for this IoT-based architecture compared to traditional offline medical devices. In this architecture the role of the sensor device is just collecting and transmitting the data, therefore no power will be consumed on local data processing. The wireless transmission occurs with a nearby edge device that minimizes the radio transmission power consumption. The computation, detection, and diagnosis happen on the cloud server, where the data from every other patient is available for comparison and learning. This feature provides collective knowledge for all patients, ensuring that each decision is enriched by the new data being stored in the cloud database. In this architecture, both the server and the edge device can notify the patient about important health events. Additionally, the configuration of the sensor device can be updated remotely and automatically via the edge or cloud layer to match the situation, reducing sensor node power consumption and optimizing the affected parameters.

IoT-based remote health monitoring systems face significant challenges, primarily within the sensor layer, which is the most resource-constrained component of the architecture. The primary limitation in this layer is the power source, which subsequently impacts various aspects of the system's functionality. These constraints necessitate careful trade-offs in hardware selection, balancing factors such as processing power, communication range and capacity, the number of sensing components, and data quality. For instance, designers must choose between powerful or simple processing units, long-range wireless communication, or short-range alternatives, and decide whether to employ separate, accurate sensing components for each vital sign or opt for an all-in-one sensor with potentially lower confidence levels. These decisions significantly influence the system's overall performance and reliability.

The dynamic nature of patient activities and environments further complicates the challenges faced by IoT-based health monitoring systems. Unlike the controlled setting of a hospital, patients in remote monitoring scenarios engage in various activities that can affect their vital signs and the accuracy of measurements. For example, an elevated heart rate may be normal for a person exercising but concerning for someone resting at a hospital. Additionally, patient activities can introduce noise into the signals, reducing the accuracy of calculated health parameters. This variability in context and activity levels necessitates sophisticated algorithms capable of distinguishing between normal physiological responses to activity and genuine health concerns.

While hardware selection plays a crucial role in addressing the resource constraints of the sensing layer, software solutions for the sensor, edge, and cloud layers offer promising avenues for system optimization. These software-based approaches have the potential to manage the adaptation of patient models to different contexts and preserve data quality, thereby enhancing the overall effectiveness of IoT-based remote health monitoring systems. The distinction between hardware and software solutions highlights the dual nature of system resources: hardware represents static resources that are determined during the design phase, while software solutions embody dynamic resources that can be adjusted during runtime, providing adaptability and flexibility to the system. This combination of carefully selected hardware and adaptive software solutions paves the way for more robust and efficient remote health monitoring systems in the future.

This thesis addresses the challenges inherent in IoT-based remote health monitoring systems through a resource management approach, recognizing that these challenges span both static and dynamic resource domains. By adopting this perspective, a comprehensive approach is proposed to optimizing system performance and efficacy. The studies conducted within this thesis contribute several innovative hardware architectures and smart control algorithms designed to effectively manage both static and dynamic resources within these complex systems.

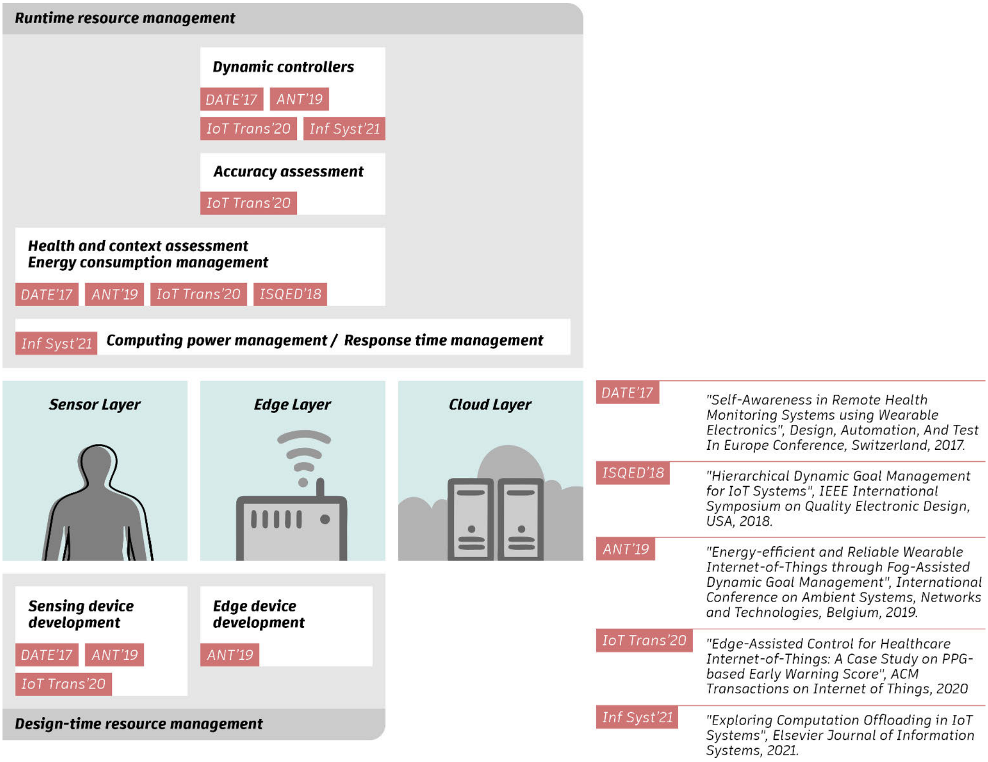

Figure 2. The overview of the thesis contributions and the topics covered in the papers.

While the primary focus of this thesis is on resource management solutions, the development of an Early Warning Score system for in-home chronic patients is considered as case study in all proposed solutions. This approach is chosen due to the proven effectiveness of Early Warning Score systems in hospital settings, where they have demonstrated significant potential in saving lives. By extending these capabilities to the home environment, the aim is to bridge a critical gap in healthcare delivery, potentially revolutionizing the management of chronic conditions and improving patient outcomes. Through the multifaceted approach to resource management, the proposed methods strive to overcome the unique challenges posed by IoT-enabled remote monitoring, ultimately contributing to the advancement of healthcare technology and the enhancement of patient care.

1.4.1 Contributions

This thesis contributes to the advancement in remote health monitoring systems through innovative resource management approaches, including:

- Examining the properties of hardware and electronic components, leading to the design and implementation of IoT-based architectures and data collection systems as static resource management approaches.

- Presenting four dynamic solutions for real-time resource management. The first solution leverages the system's self-awareness, while the second incorporates context-awareness by considering the subject's properties and their environment. The third approach addresses resource constraints and priorities by focusing on the system's goals. The final dynamic solution optimizes the allocation of computation power and response time resources based on their location in system architecture.

- Demonstrating the implementation and practical examination of both static and dynamic solutions, indicating improvements in energy efficiency, accuracy preservation in prone-to-noise contexts, priority-based resource allocation, and enhanced computation in crowded networks.

- Additionally, the thesis proposes a modified context-considered Early Warning Score system (EWS) for in-home patients.

Figure 2 presents a comprehensive overview of this thesis's contributions to IoT-based health monitoring systems. The diagram illustrates the research outputs categorized into runtime and design-time resource management strategies mapped onto the system's architectural layers. Each contribution is labeled with its corresponding publication, demonstrating how the work addresses specific challenges across the system's components.

The following chapter of this thesis outlines the preliminary terms of the study field. It begins with an overview of health IoT and then delves into remote patient monitoring, including its components and architecture. Chapter 2 then proceeds to explain the Early Warning Score system and the basics of biosignals and provides a comprehensive description of the Photoplethysmogram signal as a rich source for gathering essential medical parameters.

Chapter 3 explains and categorizes the type of system resources. It then presents the static resources employed in designing the hardware components within the studies contained in this thesis as a resource management approach at design time. Finally, it describes the brief of the proposed runtime resource management solutions and models.

Chapter 4 explores the concept of self-awareness and its application in optimizing the system to minimize sensing device power consumption and automate reasoning about the patient's health situation. The proposed model includes situation awareness, which considers the patient's activities and environment, a self-aware core that takes into account the patient's characteristics, and an attention component that prioritizes the actions taken. This approach is presented in Paper *III*.

Chapter 5 details a dynamic resource manager that regulates the sensing component based on the patient's activity and health status. The outcome is a dynamic service at the edge layer that balances energy efficiency and measurement accuracy. This solution, along with the developed sensor node and the architectural design, is presented in Paper *I*.

Chapter 6 discusses the concept of goal management and its use in managing resources for an IoT-based wearable system. The goals of a multi-goal system are the patient's health status, continuous monitoring, and accurate data, which are managed through dynamic observation based on defined policies and priorities. The concept, the management method, and the description of the developed remotely reconfigurable sensor node are presented in Paper *II* and Paper *IV*.

Chapter 7 introduces a method for managing computational power and response time. The solution starts by formulating the behavior of a complex multi-sensor IoT system and then proposes a dynamic computation offloading algorithm. The model and the proposed dynamic offloading solution are detailed in Paper *V*.

Chapter 8 presents the latest advancements in health technology and potential pathways for future work, Chapter 9 concludes the thesis, and Chapter 10 provides an overview of the original publications.

2 Preliminaries

2.1 Healthcare Internet of Things

The vast network of interconnected devices known as the Internet of Things (IoT) is transforming numerous industries, and the healthcare sector is not exempt from this trend. Healthcare Internet of Things creates a specialized ecosystem where medical devices, sensors, and systems communicate and exchange health data over networks. This application revolutionizes healthcare delivery, patient monitoring, and medical research. [32; 33; 34]

Major applications of the Healthcare IoT are shown in Figure 3. *Remote patient monitoring*, often facilitated by wearable health devices, is a key aspect of Healthcare IoT. It allows healthcare providers to track vital signs and symptoms remotely, particularly beneficial for chronic conditions and post-operative care [35]. *Smart hospitals* leverage IoT to optimize patient care, streamline operations, and manage assets more efficiently [36; 37]. Beyond direct patient care, Healthcare IoT extends to *Environmental health monitoring*. Sensors track factors like air quality, temperature, and humidity in healthcare facilities, contributing to patient well-being and public health by monitoring community-wide environmental conditions [38]. In *Medical research*, Healthcare IoT provides unprecedented opportunities for data collection and analysis. Researchers can gather real-time, continuous data from large groups, potentially accelerating medical discoveries and improving our understanding of various health conditions [39]. Additionally, in *Healthcare administration*, IoT systems can automate routine tasks, optimize resource allocation, and provide real-time insights into facility operations and staff performance [40]. As both IoT and its healthcare-specific applications continue to evolve, they are expected to have an increasingly profound impact on healthcare delivery. The convergence of these technologies with advancements in computation methods and the expansion of connected devices networks promises even more possibilities, shaping the future of healthcare improvement and maintenance.

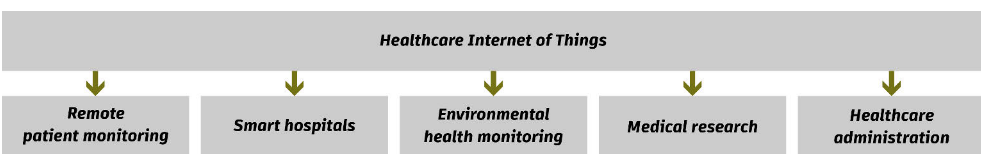

Figure 3. Major applications of healthcare Internet of Things.

2.2 IoT-enabled Remote Patient Monitoring

A remote health monitoring system based on the Internet of Things (IoT) leverages connected devices to continuously collect and transmit a patient's vital signs and send them to cloud-based platforms through wireless technologies [41; 42].

A typical IoT-based health monitoring system integrates hardware and software components to collect, transmit, analyze, and present health data. As illustrated in Figure 4, the system architecture consists of several interconnected layers. The hardware components form the physical backbone of the system. Battery-operated sensors and wearables directly collect health metrics (e.g., heart rate, respiration rate, and blood oxygen saturation) from the patient and send data to edge devices via wireless communication modules. Edge devices like smartphones or dedicated hubs act as local agents for aggregation, processing, and analysis of the collected data. The information then travels through network interfaces to cloud servers, which store and process large volumes of health data, manage the services, and provide access for system users. Additionally, a collection of interface devices provides access, information, and notifications for the patient and healthcare providers.

Complementing this hardware is a suite of software components. Embedded software and services run on sensors to collect data and transmit data. The edge devices run local processing and dynamically apply system management algorithms. In the cloud, data analytics services use advanced algorithms to derive insights from the collected health data. Assessment and management modules interpret these insights, generating alerts and aiding in patient care. Cloud platforms host these operations and often include APIs for integration with other healthcare systems. User interfaces, including web and mobile applications, wearables displays, and sensor indicators, present information to patients and healthcare providers in an accessible format. Data access security, secure data storage, and encrypted communication ensure data protection and smooth data transmission throughout the system. This integration of hardware and software enables continuous health monitoring, facilitating timely interventions and personalized care. The layered architecture allows for scalability while distributing processing across edge and cloud components optimizes performance. By bridging the physical and digital aspects of healthcare, these systems support more proactive and patient-centered care delivery. They allow for real-time monitoring, early detection of health issues, and data-driven decision-making for healthcare providers.

2.3 Early Warning Score

Over two decades ago, a compelling body of evidence emerged, drawing the attention of medical professionals to the critical progression of adverse events in hospital wards that often culminated in mortality or permanent impairment in intensive care

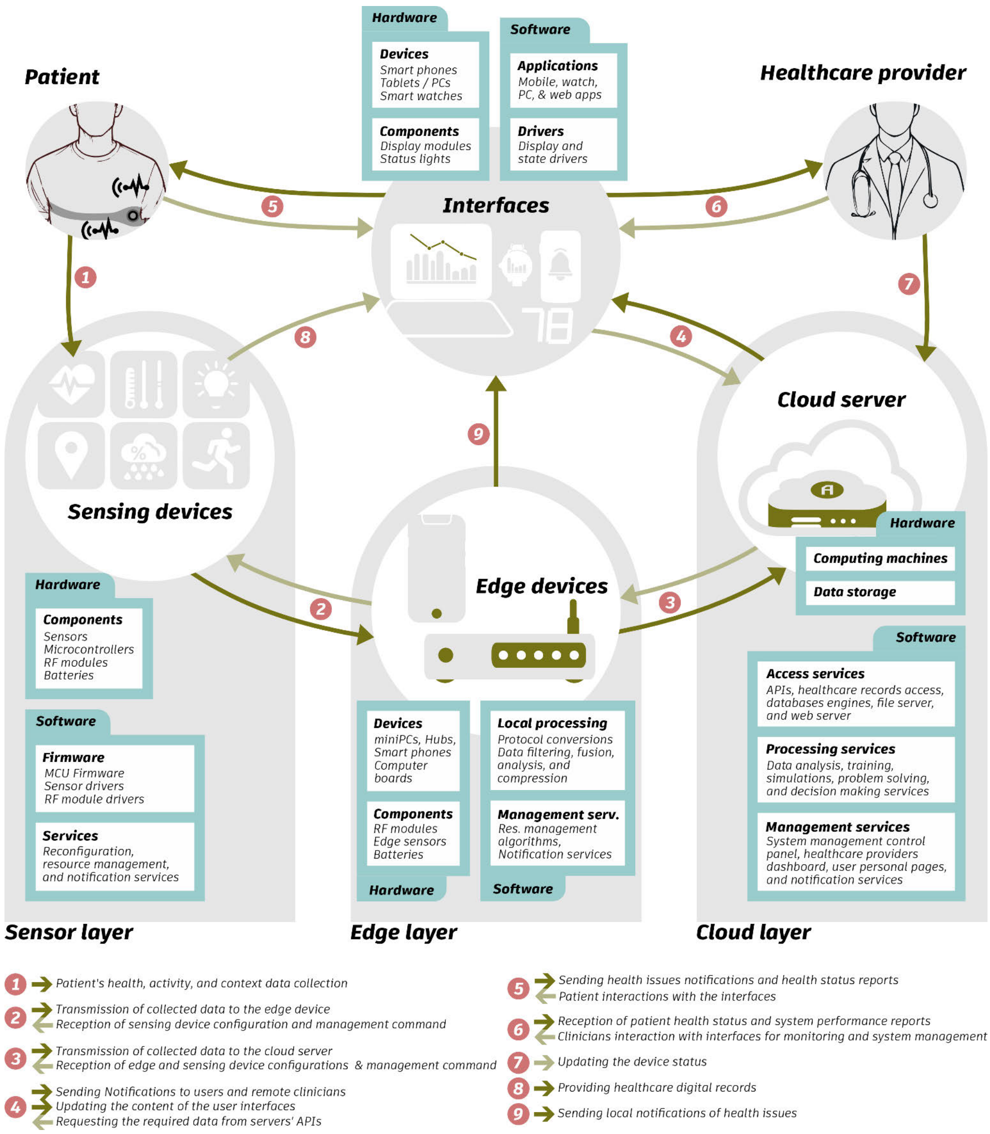

Figure 4. The architecture of Internet of Things-enabled remote patient monitoring indicating the hardware and software components of layers and sections.

units [43; 44; 45]. The research highlighted a crucial finding: the presence of at least one aberrant value in a patient's vital signs within the 24-hour period preceding clinical deterioration. Subsequent studies and clinical practices demonstrated that vigilant patient monitoring and adherence to specific guidelines could effectively prevent these adverse events, leading to a reduction in unanticipated ICU admissions and unexpected deaths. In response to this growing understanding, Morgan et al. introduced the Early Warning Score (EWS) in 1997 [46], a pioneering scoring method for evaluating patients' vital signs and facilitating early recognition of deterioration symptoms. Since its inception, the EWS methodology has been widely adopted by hospitals globally, consistently demonstrating its efficacy in predicting adverse events and mitigating their undesirable consequences [47; 48; 49; 50]. This approach has not only revolutionized patient care but also significantly contributed to the advancement of preventive strategies in clinical settings, underscoring the importance of early intervention in improving patient outcomes.

The proliferation of Early Warning Score (EWS) systems has led to a diverse array of methodologies currently in use across the global healthcare landscape. Healthcare institutions and national health systems have customized and refined the original EWS concept to align with the specific physiological characteristics of their patient populations and to reflect their unique outcome statistics. This process of adaptation has resulted in numerous variants of the EWS, each tailored to meet the particular needs and contexts of different healthcare settings [52]. Despite this diversity, these various EWS methods generally adhere to a common fundamental principle. They all aim to identify early signs of patient deterioration through the systematic evaluation of vital signs and other clinical parameters.

Medical Early Warning Score (EWS) systems typically comprise a table and a set of instructions. The table contains rows for various vital signs, with each row divided into value ranges corresponding to scores from 0 to 3. A score of 0 indicates normal values, while 3 represents the most significant deviations from the norm. The accompanying instructions outline a protocol for periodic vital sign measurements, calculation of an overall patient score, and adjustment of measurement intervals based on this score.

In basic EWS versions, a nurse measures and records a patient's heart rate, respiration rate, body temperature, blood oxygen saturation, and blood pressure—the five primary vital signs. Each vital sign is assigned a score by referencing the EWS table, and these individual scores are summed to produce an overall score. The EWS instructions then dictate the appropriate course of action based on this overall score. For scores near 0, the standard monitoring schedule is maintained. As the score increases, the frequency of check-ups may be increased, medical experts

Table 1. A conventional Early Warning Scores (EWS) chart [51].

Score	3	2	1	0	1	2	3
Heart rate[1]	≤39	40-50	51-59	60-100	101-110	111-129	130≥
Systolic BP[2]	≤69	70-80	81-100	101-149	150-169	170-179	180≥
Respiratory rate[3]		≤8		9-14	15-20	21-29	30≥
Body temperature[4]		≤35		35.1-38		38.1-39.5	39.6≥
SpO_2 (%)	≤84	85-89	90-94	95-100			
Consciousness Level				Alert	Voice[5]	Pain[5]	Unresponsive

[1]beats per minute, [2]mmHg, [3]breaths per minute, [4] °C, [5] Reacting to voice and pain

may be called to examine the patient, and in cases of high scores, the patient may be transferred to the intensive care unit (ICU). Effective implementation of EWS requires a dedicated team of medical professionals, often referred to as a Rapid Response Team (RRT), Patient at Risk Team (PART), or Critical Care Outreach Service (CCOS). Extensive research on EWS outcomes has demonstrated significant reductions in cardiac arrests, cardiopulmonary resuscitation (CPR) in ICU, and mortality [54].

Given its maturity, widespread adoption in hospitals worldwide, and proven efficacy in predicting and preventing severe adverse events, the EWS method serves as a standard for assessing patient health conditions in this thesis. The primary objective is to adapt this method for remote monitoring of in-home patients. However, implementing EWS for an in-home patient presents several challenges. A key issue is the variation in vital sign values during daily activities compared to those defined in the EWS table for hospitalized patients, who are often bedridden. In-home patients are typically more active, leading to naturally higher heart rates and blood pressure in healthy conditions. Moreover, environmental factors can influence vital signs. For instance, blood pressure, normally measured in a controlled hospital environment, may be elevated in cold conditions or lowered in warm weather outside the hospital setting. These scenarios result in different EWS scores for in-home patients compared to hospitalized individuals, reflecting genuine changes in vital signs due to activity and environment. Additionally, these factors can sometimes cause measurement devices to register incorrect values. For

Table 2. A general Early Warning Score instructions [53].

EWS	Frequency of monitoring	Clinical response according to escalation protocol
0-1	Min. 12 hourly	• Continue monitoring minimum 12 hourly
2	Min. 6 hourly	• Assess airway, breathing, and circulation and intervene appropriately • With individual score = 2 inform nurse in charge about patient
3-5	Min. 4 hourly	• Assess airway, breathing and circulation and intervene appropriately • Nurse in charge informs on-call physician, who assesses patient and lays out appropriate treatment and/ or diagnostic plan
6	Min. 4 hourly	• Assess airway, breathing and circulation and intervene appropriately • Urgent assessment by on-call physician, who assesses patient and lays out appropriate treatment and/ or diagnostic plan
7-8	Min. 1 hourly	• Assess airway, breathing and circulation and intervene appropriately • Emergency assessment (within 30 minutes) by an on-call physician, who assesses patient and lays out appropriate treatment and/ or diagnostic plan • Consider calling the medical emergency team (MET)
9	Min. 1/2 hourly	• Assess airway, breathing, and circulation and intervene appropriately • Emergency assessment (within 15 minutes) by an on-call physician, who assesses patient and lays out appropriate treatment and/ or diagnostic plan • Patient must be conferred with specialist or medical emergency team (MET)

Figure 5. The flow of the biosignals analysis.

example, electrocardiogram signals used to calculate heart rate may be distorted by noise during walking or running. Similarly, skin temperature, an indicator of body temperature, can be easily affected by ambient room temperature.

The adaptation of Early Warning Score (EWS) systems for in-home patient monitoring is a key focus of the resource management studies in this thesis. To address the challenges of translating hospital-based EWS to home healthcare settings, several solutions are proposed, including adapting Early Warning Scores to patient activity and context, aiming for optimal accuracy during daily activities, and prioritizing the patient's health status as a fundamental goal of remote patient care. These solutions aim to enhance the applicability and effectiveness of EWS in home environments, potentially improving early detection of health deterioration and supporting timely interventions in non-hospital settings.

2.4 Biosignals and Photoplethysmography (PPG)

Biosignals are measurable patterns of electrical, mechanical, or chemical responses that occur during biological events or activities. The analysis of these signals provides valuable information about the underlying biological processes. This extracted information aids in understanding the function and physiological mechanisms of specific tissues or organs, facilitating the diagnosis and treatment of health issues [55]. (Figure 5)

Biosignals can be obtained through direct examination by a healthcare professional or via data acquisition devices. For instance, a physician may study heart sounds directly using a stethoscope or indirectly through a phonocardiography (PCG) device. Historically, biosignal analysis was limited to the study of analog signal plots. However, advancements in electronics and information technology have led to the development of computerized algorithms that analyze digitized versions of these signals [56]. The process of digitizing biosignals involves several steps. Initially, the signals are converted to electric potentials and amplified to fit within a specific voltage range. Noise reduction and frequency filters are applied to minimize signal distortions. An analog-to-digital converter (ADC) then samples the processed signal at regular intervals, assigning numeric values corresponding to voltage levels [57]. Microcontrollers or computers can read and store these numeric values for further analysis. The sampling frequency and bit-depth determine the quality of the digitized signal, with higher ones producing better quality but larger

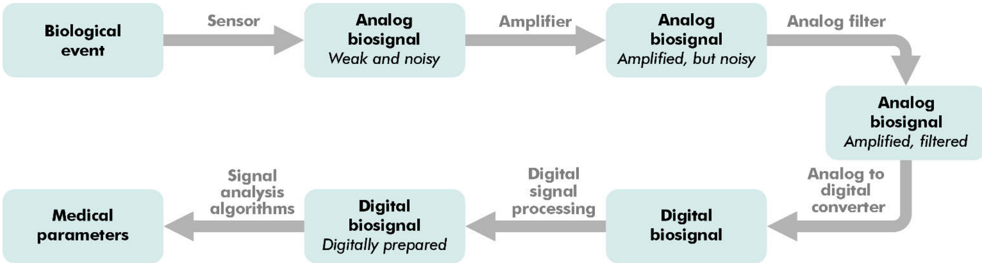

Figure 6. The process of extracting medical parameters from a biosignal.

data sizes. Once digitized, additional noise reduction and frequency filtering can be applied through computerized algorithms. Advanced data analysis techniques enable the extraction of numerous medical parameters from these high-quality digitized biosignals, significantly enhancing their utility in clinical and research applications [58]. Figure 6 shows the process of extracting medical parameters from a biosignal.

In the context of this thesis, the most essential medical parameters for the Early Warning Score (EWS) method are heart rate, respiration rate, blood pressure, body temperature, and blood oxygen saturation. These vital signs are typically derived from specific biosignals. For instance, the electrocardiogram (ECG) signal is commonly used to extract heart rate, while airflow signals are used for respiration rate, photoplethysmogram (PPG) signals for blood oxygen saturation, arm cuff pressure signals for blood pressure, and temperature signals for body temperature. It is worth noting that some biosignals can provide multiple medical parameters but with varying levels of accuracy. For example, the ECG signal, which is a high-quality source for heart rate, can also be used to obtain respiration rate but less accurately. In the same way, the PPG signal, which is a reliable source for blood oxygen saturation, can also provide accurate heart rate and acceptable respiration rate measurements. Given its richness and versatility, the majority of studies related to this thesis focus on the features, benefits, and limitations of the PPG signal, aiming to enhance and maximize its outcomes.

2.4.1 Photoplethysmography (PPG)

Photoplethysmography (PPG) is a non-invasive technique that measures changes in light intensity as it interacts with body tissues containing blood vessels [59]. The PPG signal represents fluctuations in blood volume within these vessels over heart cycles. With each heartbeat, oxygenated blood inflates arteries and capillaries, and surrounding tissues consume the oxygen. This change in blood volume and oxygen content alters the light-absorbing and reflecting properties of the tissue, affecting the intensity of reflected and absorbed light. Recording the PPG signal requires at least a light source to illuminate the body tissue and a light sensor to capture the reflection

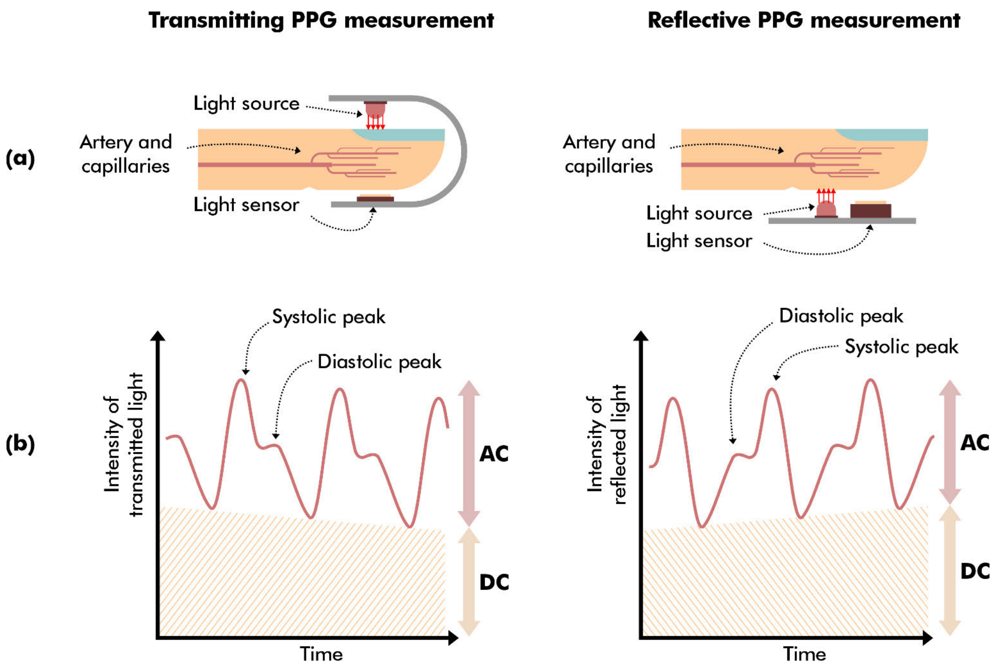

Figure 7. (a) The transmitting and reflective PPG measurement methods, (b) PPG signal shapes and AC/DC parts in transmitting and reflective methods.

or absorption [60].

Figure 7 (a) illustrates the common methods for recording the PPG signal from the finger. In the transmitting method, a light source is placed on one side of the finger, and the light sensor is positioned on the opposite side. This method records the amount of light that passes through the finger, which is the intensity of the light emitted by the source minus the amount absorbed by blood tissues. In the reflection method, both the light source and sensor are located on the same side of the finger, measuring the intensity of light reflected by blood tissues.

Figure 7 (b) shows the typical shape of a PPG signal recorded using each of the mentioned methods. The signal shape obtained through the reflection method appears to be horizontally flipped because it represents the intensity of the source light subtracted by the absorbed portion. While certain body spots like fingertips or earlobes are ideal for transmitting PPG measurements, almost any spot on the skin surface can be used for reflective PPG signals, although signal quality may vary depending on the location.

The photoplethysmogram (PPG) signal can be divided into two distinct components based on its oscillating properties. The non-oscillating component, known as the DC part, results from light reflection from body tissues rather than blood vessels. Conversely, the oscillating component, referred to as the AC part, represents the changes in the intensity of reflected light from the changing volume

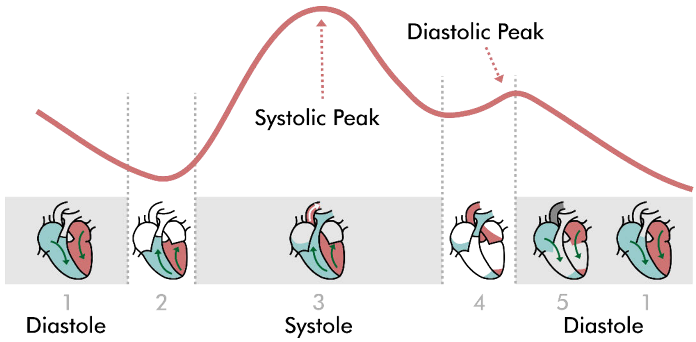

Figure 8. The PPG signal variations during the heart cycle sequences. A pulse transition delay shifts the signal to the right depending on the measurement spot.

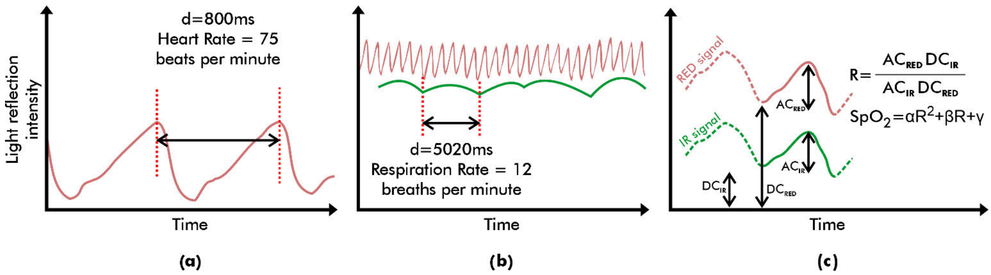

Figure 9. Vital signs extracted out of reflective PPG signal. (a) heart rate. (b) respiration rate. (c) blood oxygen saturation.

of blood vessels. Within the AC part of the PPG signal, each cycle consists of two peaks. The larger peak corresponds to an increase in blood volume during the phase of the heart cycle when the atrioventricular valves are closed, and the aortic and pulmonary valves are open. This phase, known as ventricular systole, is characterized by the heart pumping blood with maximum pressure. Consequently, this peak is labeled as the systolic peak. The second peak, termed the diastolic peak, occurs at the beginning of the diastole phase of the heart cycle. This peak is a result of a brief moment when the outgoing heart valves are closed, but the incoming valves have not yet opened. During this period, the back pressure from the capillaries causes a slight increase in blood volume, leading to the diastolic peak (Figure 8)[60].

The analysis of the AC component of the PPG signal yields several valuable medical parameters, with heart rate being the most straightforward to extract. This can be achieved by measuring the duration of a single cycle or by calculating the signal frequency using signal processing techniques (Figure 9 (a)). Further examination of the signal components, their shapes, and amplitude ratios provides additional insights into cardiovascular health, including estimates of arterial blood pressure [61], cardiac output [62], and arteriosclerosis [63].

Although the DC component of the PPG signal is generally constant, it does undergo slow changes over time. These changes occur when surrounding tissues apply pressure to blood vessels during body movements and muscle contractions. Notably, the lung inflation during breathing cycles also applies pressure to the surrounding tissues, causing the DC component to oscillate slightly with respiratory cycles. Consequently, respiration rate can be extracted from the PPG signal by filtering out high-frequency oscillations (e.g., heartbeats) and calculating the frequency of the remaining signal (Figure 9 (b)).

While certain medical parameters like heart rate and respiration rate can be obtained using a single-wavelength light source, employing a multi-wavelength light source enables the computation of additional important parameters. The light absorption coefficient of oxygenated blood cells varies with the wavelength of the emitted light, allowing for the calculation of blood oxygen saturation when two or three light sources with different wavelengths are used. The formula for calculating blood oxygen saturation involves removing the impact of the AC component by averaging peaks and valleys and then calculating the ratio of DC amplitude to averaged AC amplitude (Figure 9 (c)).

Most medical PPG sensors utilize a red light-emitting diode (LED) for heart rate measurement or a pair of red/infrared LEDs for both heart rate and blood oxygen saturation measurement. Some wearable devices also employ a green light source, either alone or in combination with red and infrared sources. Recent advancements in digital cameras and sensitive image sensors have enabled remote capture of PPG signals [64]. This method involves recording the ambient light reflected by the body skin using a digital video camera and then applying image processing algorithms to extract the PPG signal from variations in pixel brightness within the skin area.

2.4.2 PPG Limitations

The photoplethysmography (PPG) biosignal is a rich source of medical information, offering insights into various physiological parameters. However, its utilization in portable and wearable sensor devices presents certain limitations and challenges. Unlike most biomedical sensors that are passive and low-power, PPG sensors require at least one active light source, which consumes significantly more energy than passive sensors. While reducing the light source's brightness can decrease power consumption, it also increases noise, reduces signal quality, and diminishes the accuracy of extracted values. Implementing PPG sensors in wearable remote patient monitoring devices allows for compact and small form factors. However, efficient power and accuracy management becomes crucial to ensure practical and prolonged usage. This necessitates striking a balance between power consumption and signal quality to maintain accurate measurements while extending device operation time.

Another significant challenge associated with PPG signals is the susceptibility

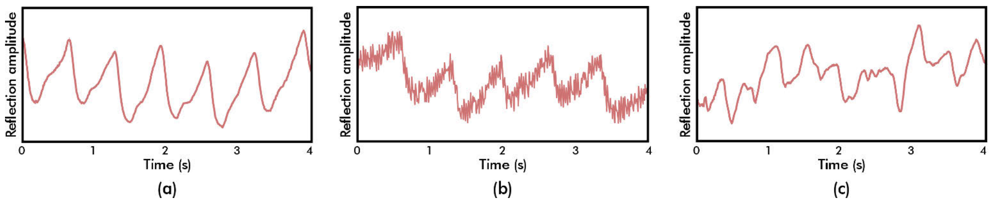

Figure 10. PPG signal quality samples collected from fingertip: (a) intense light source during sleeping (b) dim light source during sleeping (c) intense light source during running.

of the signal baseline (the DC component) to body movements. During intense physical activities, separating the AC component from the DC component becomes increasingly difficult. This movement-induced interference can lead to inaccurate heart rate measurements due to an unclear AC component and imprecise respiration rate calculations resulting from a fluctuating DC component. Figure 10 illustrates the clear and fluctuating examples of PPG signals captured during sleep and running using intense light and a noisy PPG example captured during sleeping using dim light sources.

These challenges are managed within three studies in this thesis, focusing on implementing management approaches such as self-awareness, context-awareness, and goal management in sensor design, edge control, and power management levels. The aim is to improve the reliability and practicality of PPG-based wearable devices for continuous health monitoring.

3 Resource Management in Healthcare Internet of Things System

3.1 Resources

Each component of an IoT-based remote health monitoring system can serve as a resource, a resource provider, and a resource consumer. From a resource management perspective, the building blocks of such systems can be categorized as static and dynamic resources [65]. The concept of categorizing resources in a health IoT system into static and dynamic resources provides a structured way to understand how different components require specific management strategies.

3.1.1 Static Resources

Static resources refer to physical or infrastructure-related elements of the system that remain relatively unchanged over time. The hardware components of the IoT-based remote patient monitoring system, described earlier and shown in Figure 4, are the system's static resources. These physical elements are typically managed during the system's design and deployment phases [66; 67]. Effective management of static resources involves selecting appropriate components that meet the system's performance, accuracy, energy efficiency, and durability requirements.

Key aspects of managing static resources include carefully selecting sensors, edge devices, and other hardware components to meet the application's specific requirements. This involves evaluating their efficacy and cost to ensure that the chosen hardware meets performance criteria while remaining cost-effective. Effective design and selection are crucial for building a robust health IoT system that can reliably collect, process, and transmit health data. Additionally, the strategic placement of these devices plays a vital role in ensuring optimal coverage, connectivity, operation endurance, proper precision, and environmental suitability. Proper deployment ensures that the system can function efficiently in different environmental and behavioral contexts, whether resting in a hospital, within daily activities at home, or in a remote location. Within an IoT-based system architecture, the cloud server can be categorized as a dynamic resource, even though the cloud server is a hardware component [68]. Because its capacity for communication, computing, and storage is flexible and can be changed dynamically during runtime, similar to other dynamic resources. Therefore, it can be excluded from the static resources category within the resource management paradigm.

3.1.2 Dynamic Resources

Dynamic resources of a remote health monitoring system are software-centric or data-centric components that fluctuate over time based on system demands, such as computing power, memory, network bandwidth, data, and software applications. Unlike static resources, which are fixed once deployed, dynamic resources change actively during the system's runtime [66; 67]. Effective management of these dynamic resources is crucial when the system is expected to be responsive and adaptable to changing conditions and requirements.

Key aspects of managing such resources include observing the status of the system and its resources continuously, determining the optimal consumption rate of each resource for the best performance, and dynamically allocating them to achieve the desired outcome. This involves a level of awareness about the system and its context and a system controller to continuously adjust the system configurations based on different tasks, current demands, and priorities. This dynamic allocation can include switching between static resources, load balancing, task scheduling, and task offloading. Such dynamic approaches are expected to improve the performance, endurance, accuracy of data, and quality of results in remote patient monitoring.

3.2 Resource Management at Design Time

The resource management approach applied during the design time involves selecting the proper static resources. Figure 11 shows the hardware components of a typical sensing device communicating wirelessly with an edge device.

The proposed solutions for resource management in this thesis require the sensing device to capture not only the biosignals but also the subject's activity, the properties of the environment, and, in some cases, the subject's geographical location. Therefore, the architecture of the sensing device shows various types of sensors on both the sensing device and the edge device. The following three subsections explain the primary static components of the system, which include sensors, microcontrollers, and wireless communication modules, and list the specific components used in the proposed solutions as contributions to managing the system resources during the design phase.

3.2.1 Sensors

A sensor is technically an electrical component that detects and responds to a physical stimulus, such as heat, light, sound, pressure, or motion and converts it into

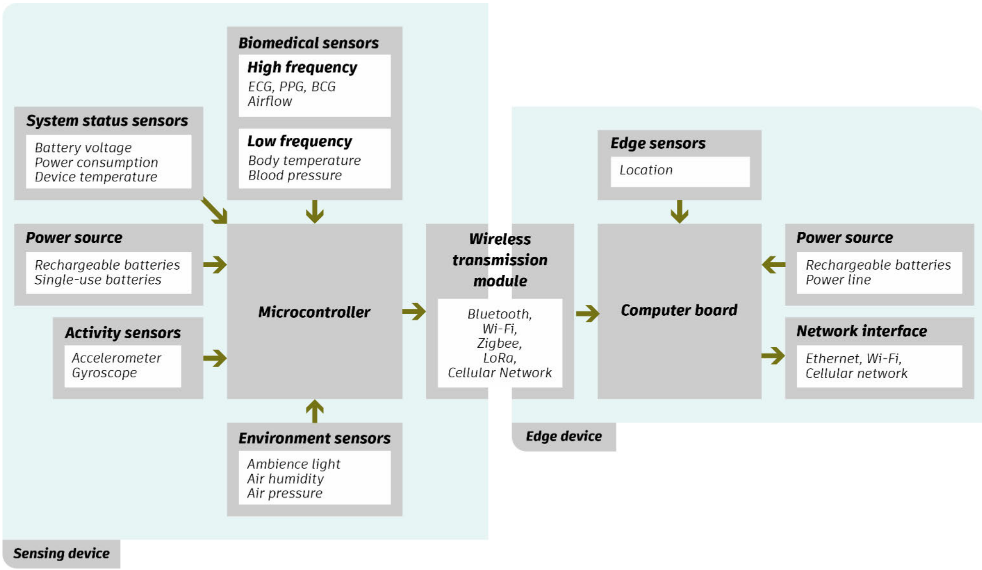

Figure 11. The typical hardware components of sensing and edge devices in a remote health monitoring system.

an electrical signal that can be measured or recorded [69; 70].

From the energy consumption perspective, sensors can be divided into two major categories: passive and active [69]. Passive sensors detect and respond to environmental stimuli without requiring an external power source to operate. They gather information by measuring natural or ambient energy, such as light, heat, or pressure, and convert these measurements into an electrical signal. Examples of passive sensors include thermistors, which change resistance based on temperature, and photodiodes, which generate a current in response to light. In contrast, active sensors require an external power source to operate and actively transmit a signal into the environment. These sensors emit energy, such as electromagnetic waves or sound, and measure the response that returns after interacting with the target. Examples of active sensors include PPG sensors, which emit light to the skin and measure the amplitude of the reflection, and radar systems that emit radio waves to detect objects.

Key specifications of sensor components include measurement range, output range, output type, response time, and accuracy. The measurement range defines the minimum and maximum values of the physical quantity that the sensor can accurately measure and is typically specified in terms of the physical quantity. Conversely, the output range determines the minimum and maximum voltage or current levels that the sensor can produce in response to the input. For instance, an analog temperature sensor might output a 0 to 5 V voltage range corresponding to a temperature range of 0°C to 100°C. The sensor type defines the output signal, whether it's analog or digital. An analog sensor produces a measurable signal proportional to the measured physical quantity. Response time is the time the sensor takes to respond to a change in the measured quantity. It is an important specification for applications requiring quick measurements. For instance, the DHT-11 humidity and temperature sensor has a response time of one second, meaning it takes that long to reach the final output value after a sudden temperature change. In contrast, a digital sensor produces a discrete numerical output by internally converting the analog signal to digital values. A parameter is explicitly defined for digital sensors as sensor resolution representing the number of bits for each sample. For example, a digital sensor with a 12-bit resolution can produce 4096 distinct output values. Digital sensors may provide a single value on each call or generate a stream of samples. Therefore, sampling frequency also may be specified as a characteristic of digital sensors. The output of a digital sensor is receivable by a microcontroller via different serial communication protocols, including I^2C (Inter-Integrated Circuit), SPI (Serial Peripheral Interface), and UART (Universal Asynchronous Receiver/Transmitter). An analog sensor transfers output signal via a single wire, while digital sensors use two wires on I^2C protocol (SDA and SCL), two wires on UART protocol (TX and RX), and four wires on SPI protocol (MOSI, MISO, SCK, and CS). A typical digital sensor also has internal configurable registers that enable it to be used in various configurations. Configurable parameters include working modes, the power consumption of the active component, sampling frequency, averaging, sample resolution, and the number of parameters to measure or report.

Table 3 shows the types and specifications of the sensors used within the proposed solutions in this thesis. Based on the specifications, different types of sensors exhibit varying power demands.

3.2.2 Microcontrollers

A microcontroller unit (MCU) is a self-contained, highly integrated semiconductor chip that incorporates the key components of a full-sized computer [71]. Just like a computer, an MCU consists of a central processing unit (CPU) responsible for executing instructions and performing arithmetic and logical operations. It also includes both volatile memory (RAM) for temporary data storage and non-volatile memory (ROM, EEPROM, or flash) for storing the program code and persistent data. MCUs are equipped with dedicated input/output (I/O) peripherals that allow them to interface with external devices, sensors, and actuators, enabling interaction with the real world. Built-in timers and counters are often included for generating precise time delays, measuring elapsed time, and controlling pulse-width modulation (PWM) signals. An interrupt controller enables the MCU to respond to external events or conditions asynchronously, ensuring efficient and

Table 3. Specifications of the sensors utilized in the development of sensing devices during design-time resource management.

Sensor / Manufacturer / Component No.	Sensor type and Specifications	Measurement
Heart rate, **SpO_2** Cooking Hacks	Active, Digital 8-wire interrupted decoder 8-bit, 1 Hz SpO_2: 70% to 100%, Heart rate: 35 to 220 bmp, *	Red light (660 nm) intensity, Infrared light (940 nm) intensity
Airflow Cooking Hacks	Passive, Analog, **	Thermistor resistance changes between inhale and exhale airflow, amplified 50x
Blood pressure Vernier	Passive, Analog 0 to 258 mmHg, 2 mA 5 V	Pressure changes of the air in an inflating arm cuff
Body temperature Cooking Hacks	Passive, Analog, 25 to 50 Ω **	Resistance changes, amplified 5x
Humidity, **Temperature** Universal-Solder Electronics DHT-11	Passive, Digital, 1-wire 8-bit, 1 Hz 20 to 90 %RH (±5%RH) 0 to 50 °C (±2 °C), 0.5 mA 3 V	Resistance changes due to variations in humidity and temperature
Ambient light Advanced Photonix PDV-P8001	Passive, Analog 3 to 200 KΩ, **	LDR resistance changes due to variations in light intensity
Acceleration Analog Devices ADXL362	Passive, Digital, SPI 12-bit, 400 Hz ±2 g to ±8 g, 1.8 μA 2 V	Acceleration in 3 directions
PPG Analog Devices MAX30102	Active, Digital, I^2C 15-bit to 18-bit, 50 Hz-3200 Hz LEDs current programmable from 0 to 50 mA	Red light (660 nm) intensity, Infrared light (880 nm) intensity
PPG Analog Devices MAX30105	Active, Digital, I^2C 15-bit to 18-bit, 50 Hz-3200 Hz LEDs current programmable from 0 to 50 mA	Red light (660 nm) intensity, Infrared light (880 nm) intensity, Green light (537 nm) intensity
Acceleration NXP Semiconductors MMA8451Q	Passive, Digital, I^2C 8-bit & 14-bit, 1.5 Hz-800 Hz ±2 g to ±8 g, 24 to 165 μA 2.5V	Acceleration in 3 directions
Temperature Texas Instrument TEMP102	Passive, Digital, I^2C 12-bit, 80 Hz –25 °C to 85 °C (±2), 10 μA 2.5 V	Voltage changes in a diode due to variations in temperature
Temperature Microchip MCP9808	Passive, Digital, I^2C 12-bit, 4 Hz-13 Hz -40 °C to 125 °C (±0.25), 200 μA	Voltage changes in a diode due to variations in temperature
ECG Polar Polar T31	***, Analog	Voltage changes that represent heart electrical activities
Accelerometer **Gyroscope** **Magnetometer** **Compass** TDK MPU9250	Passive, Digital, I^2C & SPI 16-bit, 3.9 Hz-8000 Hz ±2 g to ±16 g ±250 dps to ±2000dps ±4800 μT, 0.28 to 3. 7 mA 2.5 V	Linear and angular acceleration, magnetic fields, and computed compass direction

Color guide and notes:

- Sensing parameter(s)
- Manufacturer
- Component number
- Sensor type: Active or Passive
- Sensor type: Analog or Digital
- Digital communication protocol
- Digital sample bit depth
- Sampling frequency
- Measurement range
- Current consumption
- * Commercial device, consumption properties undisclosed
- ** Passive component, negligible power consumption
- *** A commercial wireless chest strap, reads ECG signal passively and transmits actively

responsive operation. Many MCUs incorporate an analog-to-digital converter (ADC) that allows them to process analog signals from sensors and convert them into digital values. Standard communication protocols like UART, SPI, and I^2C are commonly integrated into MCUs, facilitating their interface with other devices and peripherals. Key characteristics of MCUs include their small size, as they are highly integrated and miniaturized, often in a single chip or package, making them suitable for embedded applications with limited space. MCUs are designed to operate efficiently, consuming minimal power, which is crucial for battery-powered and energy-constrained applications. The high level of integration and mass production of MCUs contribute to their cost-effectiveness, making them suitable for a wide range of applications. Most importantly, MCUs are programmable to perform specific tasks, optimizing their performance for many applications, including data collection for health monitoring purposes. The proposed systems in this thesis use two types of microcontrollers due to their suitable features and prototyping flexibility.

MCU

The ATmega328P is a high-performance, low-power 8-bit microcontroller manufactured by Atmel company [72]. It is based on the AVR RISC architecture, enabling efficient instruction execution with a throughput of up to 20 MIPS at a maximum clock speed of 20 MHz. The microcontroller resources include 32 KB of in-system programmable flash memory, 2 KB of SRAM, and 1 KB of EEPROM, allowing for flexible data storage and program execution. The ATmega328P includes 23 programmable I/O lines, making it versatile for various applications. It is equipped with multiple peripherals, including two 8-bit timers, one 16-bit timer, a 10-bit ADC with up to eight channels, and a programmable serial USART for communication. Additionally, it supports various power-saving modes, making it suitable for battery-operated devices. The operating voltage range is from 1.8V to 5.5V, and it can function in temperatures ranging from -40°C to +105°C. The ATmega328P's combination of features and low power consumption makes it an ideal choice for embedded control applications in IoT devices.

The ATmega328P microcontroller has several working modes, each with a different power consumption rate. Since the chip works with a wide range of input voltages and CPU clock speeds, the power consumption of each mode changes accordingly. When powered via a 3.3 V input voltage in Active mode, the ATmega328P requires 1 mA to 6 mA current when operating at 2M Hz to 20 MHz. In the same condition, in Idle mode, it requires 0.1 mA to 1.25 mA, and in Power-down mode, it requires less than 1 uA. In Idle mode, most peripherals are running, but the CPU is stopped. In power-down mode, all peripherals are stopped, and the internal oscillator is off.

ESP Module

The other utilized microcontroller is ESP8266-12E, which has more integrated resources, including a 32-bit microcontroller capable of operating at clock speeds of 80 MHz and 160 MHz, 4 MB of flash memory for program storage, along with 80 KB of instruction RAM, and 32 KB of data RAM for execution and data storage [73]. Like ATmega328P, it has various peripherals such as a 10-bit ADC, multiple GPIO pins, and support for communication protocols like UART, SPI, and I^2C.

In addition to the MCU functionality, the ESP8266-12E incorporates a complete Wi-Fi networking solution. It supports IEEE 802.11 b/g/n Wi-Fi standards and can operate in multiple modes: Access Point (AP), Station (STA), or both simultaneously. The module also includes an integrated TCP/IP protocol stack, enabling easy integration of Wi-Fi functionality into embedded systems. With its compact size and low power consumption, the ESP8266-12E is designed for IoT and embedded applications that require both microcontroller capabilities and Wi-Fi connectivity. The combination of a 32-bit MCU, Wi-Fi functionality, and various peripherals on a single chip makes the ESP8266-12E a versatile and cost-effective solution for developing connected devices.

Due to its integrated wireless transmission module, the ESP8266-12E consumes more power than the ATmega328P. In the active mode, when both the Wi-Fi modem and CPU are working, the microcontroller requires around 70 mA current to operate. However, in Modem Sleep mode, the Wi-Fi modem is in a low-power state while the CPU and other components remain active, consuming around 15 mA. Light Sleep mode stops the CPU but keeps the Wi-Fi modem and some peripherals running, reducing power consumption to approximately 0.9 mA. For the lowest power consumption, Deep Sleep mode powers off most components except for the real-time clock (RTC), drawing as little as 10 μA.

3.2.3 Wireless Communication Modules

Wireless communication modules are the pipelines of IoT sensing devices, enabling them to collect and transmit data to remote locations [74]. These compact components integrate hardware, firmware, and software to facilitate wireless connectivity using technologies like Wi-Fi, Bluetooth, Zigbee, LoRa, or cellular networks. The design-time resource management of an IoT-based health monitoring system also includes the choice of the wireless module. The selection depends on factors such as data transmission range, power consumption, data rate, and network infrastructure. For instance, short-range applications like smart homes often utilize Wi-Fi or Bluetooth, while long-range, low-power scenarios, such as environmental monitoring, may leverage LoRa or cellular technologies.

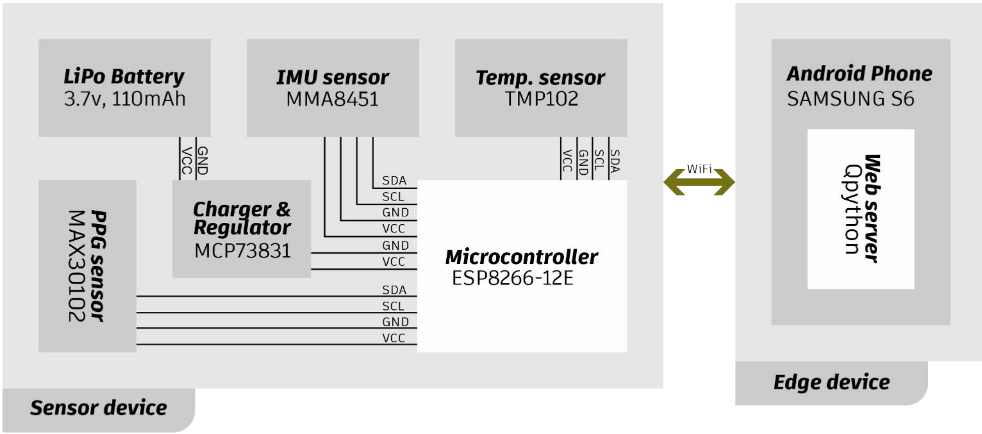

Figure 12. The block diagram of the developed sensing device utilizing ESP8266-12E Wi-Fi module

The proposed sensing devices in this thesis use three types of wireless communication modules considering the power consumption of the provider modules, the reconfigurability of the module, the data rate of the transmission protocol, and the availability of the technology in the required edge device.

Wi-Fi

Wi-Fi is a wireless local area network (WLAN) technology that operates on the 2.4 GHz and 5 GHz frequency bands [75; 76]. It's designed to provide high-speed, high-data-rate connectivity for devices that need to communicate with each other over medium to long distances, typically up to several hundred meters. Thanks to advanced modulation techniques, Wi-Fi has a high data transmission rate, typically around 150 Mbps to 1.9 Gbps, which is sufficient for many high-bandwidth applications. However, this comes at the cost of higher power consumption, which is typically in the range of 100-500 mW. Wi-Fi devices use a variety of mechanisms to protect against unauthorized access and eavesdropping.

Wi-Fi supports various network configurations, including infrastructure mode, where devices connect through a central access point (like a router), and ad-hoc mode, where devices connect directly to each other. This flexibility allows for communication distances ranging from a few meters to several hundred meters, depending on the environment and Wi-Fi technology used. The Wi-Fi-based sensing devices designed and developed within this thesis utilize the ESP8266-12E Wi-Fi module mentioned earlier for its embedded programmable microcontroller (Figure 12).

Bluetooth Low Energy (BLE)

Bluetooth Low Energy (BLE) is a wireless personal area network (PAN) technology designed for low-power, short-range communication [77; 78]. Operating in the 2.4 GHz frequency band, it provides connectivity for devices within approximately 100 meters. BLE employs specialized techniques to minimize power consumption, such as low transmit power and intermittent operation, enabling extended battery life. A typical BLE device consumes around 5-10 μA of current in sleep mode and around 10-20 mA of current during data transmission, which makes BLE devices ideal for applications where battery life is a critical consideration. Its robust architecture ensures reliable data transfer in challenging environments. The data transmission rate of BLE is typically around 1-2 Mbps, which is sufficient for many low-power applications. BLE supports various device roles, including central and peripheral modes. BLE devices use a variety of mechanisms to protect against unauthorized access and eavesdropping and a whitelisting technique to ensure that only authorized devices can connect to a central device. These characteristics make it suitable for a wide range of applications, from simple sensor networks to complex IoT systems. The NRF51822 BLE module was utilized for the sensing devices developed in the studies included in this thesis.

The nRF Transmitter

The nRF24L01+ is a low-power, 2.4 GHz wireless transceiver module developed by Nordic Semiconductor, designed for short-range communication in various applications, including IoT devices [79]. The module supports configurable data rates of 250 kbps, 1 Mbps, and 2 Mbps, allowing for flexibility based on application requirements. It features a multi-channel capability, enabling communication over 125 independent channels, which can be utilized simultaneously by multiple devices using the same frequency. The nRF24L01+ employs an enhanced protocol for efficient packet transmission, ensuring that sent packets are received correctly. During transmission, nRF24L01+ consumes approximately 12 mA at 0 dBm output power, while in standby mode, it draws only 26 µA. In power-down mode, the current consumption can be as low as 900 nA, significantly extending battery life. The module communicates with microcontrollers via the SPI interface, making it easy to integrate into various projects without extensive wireless design knowledge. Overall, the nRF24L01+ is a versatile and efficient solution for implementing wireless communication in low-power applications. The nRF24L01+ module was utilized for the sensing device developed in Paper *II* included in this thesis (Figure 13).

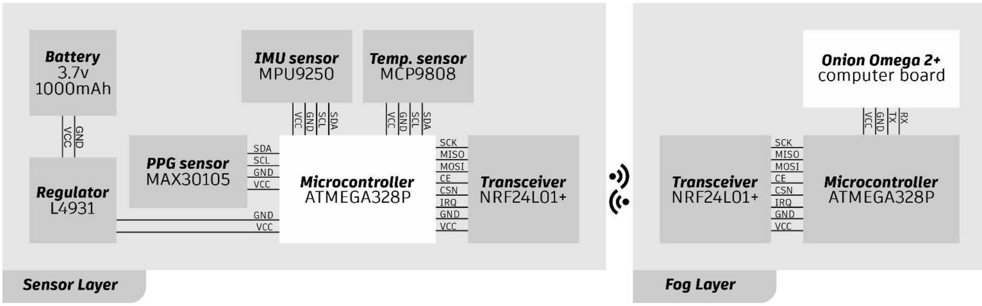

Figure 13. The block diagram of the developed sensing device utilizing nRF24L01+ module.

3.3 Resource Management at Runtime

Resource management during the runtime means the utilization of suitable approaches for allocating the right amount of resources to the right resource consumer at the right time. Moreover, it means designing efficient configurations that can be changed responsively when the system condition changes. Switching between the various configurations defines the site, the size, and the schedule for the consumption of a specific resource. This thesis investigates the management of dynamic resources via four different approaches.

3.3.1 Self-awareness

Self-awareness refers to the system's ability to monitor, analyze, and adapt its own components and behaviors in real time based on changing conditions and requirements. This approach enables the system to autonomously assess its performance, resource utilization, and environmental factors, allowing it to make informed decisions about resource allocation, optimization, and reconfiguration. A self-aware system can dynamically adjust its applications, data analytics algorithms, and communication protocols to improve its ability to respond to user needs and environmental changes. This capability is essential for maintaining optimal operation in remote monitoring applications, where conditions can vary significantly and require timely adjustments to software resources. Chapter 4 describes this approach in detail.

3.3.2 Context-awareness

Context-awareness in an IoT-based remote monitoring system refers to the ability to recognize and respond to environmental conditions and operational contexts in real time. This approach enables the active management of dynamic resources, such as data accuracy and energy, by utilizing contextual information for informed decision-making. When high data accuracy is essential, such as in health monitoring, the system can prioritize precise measurements, even if this increases resource consumption. Conversely, in less critical situations, the system can reduce resource consumption by opting for lower-accuracy data or less frequent updates. By leveraging context-awareness, the IoT system optimizes its operations based on real-time conditions, balancing data quality with resource efficiency. A detailed explanation of this approach is provided in Chapter 5.

3.3.3 Goal Management

Goal management in an IoT-based remote patient monitoring system refers to the systematic approach of aligning and prioritizing multiple objectives to effectively manage dynamic resources. In this context, the system operates as a multi-goal framework with specific aims: ensuring on-time response in emergencies, achieving accurate measurement of vital signs when needed, and optimizing battery endurance while maintaining uninterrupted measurements. By effectively managing these goals, the IoT system can dynamically allocate its dynamic resources, ensuring that it meets the critical demands of remote patient monitoring while maintaining efficiency and responsiveness. This approach enhances the system's overall effectiveness, allowing it to adapt to varying conditions and requirements in real time. Chapter 6 offers a comprehensive overview of this approach.

3.3.4 Computation Offloading

Response time and computational power are critical dynamic resources in large-scale remote health monitoring systems that must be effectively managed, especially in congested network conditions. Computation offloading in such systems refers to the approach of redistributing computational tasks to different layers of the system architecture to optimize performance and resource utilization. When the system detects high traffic or resource constraints, it can offload computational tasks to more capable layers, such as cloud servers or edge devices. This offloading allows for quicker processing and timely responses, ensuring that critical functions are executed without delay. By observing the operational context and network conditions, the system can dynamically decide when and where to offload computations, balancing the load across available resources. This capability enhances the overall responsiveness of the system while optimizing the use of computational power, ultimately leading to improved efficiency and user satisfaction in remote patient monitoring applications. Chapter 7 offers a thorough examination of this approach.

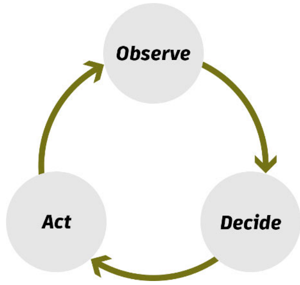

Figure 14. The schematic of ODA decision-making loop.

3.3.5 ODA Decision Model

The *Observe-Decide-Act* (ODA) loop is a key decision-making model (Figure 14) utilized within the mentioned approaches for managing dynamic resources in IoT-based remote monitoring systems [80]. It enables awareness in complex systems, ensuring optimal performance, reliability, and sustainability in resource-constrained environments. By observing the system's state, making informed decisions, and taking actions, the ODA loop allows systems to adapt to changing conditions. Its applications span IoT devices, autonomous systems, and large-scale industrial processes, facilitating intelligent resource allocation and optimization. Implementing this framework enhances autonomy and resilience, leading to improved performance and sustainability.

Observe

This initial stage involves comprehensive data collection through the system's sensor network. The system gathers information from two primary sources: internal parameters of the device or system itself and external data from the monitoring subject and surrounding environment. This stage is vital as it provides the system with an up-to-date, accurate representation of its current state and environment, forming the foundation for subsequent decision-making.

Decide

In this phase, the system processes the collected data to conclude a decision. In a health monitoring system, the decision-making process involves two main components: evaluating the subject's health and assessing the system's own operational status. The system considers potential inaccuracies or ambiguities in the data during this evaluation. Based on this analysis, the system determines the optimal configuration to address both the subject's monitoring needs and its own operational efficiency. This stage is critical for balancing the often competing demands of effective monitoring and system performance.

Act

The final stage involves implementing the decisions made in the previous phase. Based on the identified needs and optimal configuration, the system adjusts various operational parameters such as sensor sampling rates, sleep mode durations, and precision levels. These adjustments are then sent to the sensing device, which enacts the new configurations. This stage translates the system's decisions into physical actions, allowing it to adapt its behavior in response to changing conditions and requirements.

By continuously cycling through these stages, the ODA loop enables systems to maintain optimal performance and adapt to dynamic environments, making it a powerful framework for implementing awareness in various applications. It's important to note that a system needs to have a model of itself to achieve awareness, and this model can reflect the system accurately only when the user provides feedback. Each interaction contributes to forming a more comprehensive model of the system and its environment.

The following chapters offer a detailed explanation of the runtime resource management approaches mentioned earlier and the application of the ODA model in this context. These chapters provide an in-depth analysis of each approach's implementation and effectiveness in managing system resources of an IoT-based remote health monitoring system during runtime.

4 Resource Management Through Self-Awareness

Self-awareness is an essential attribute of a system, enabling it to continuously and independently monitor and interpret its own operational states, performance metrics, limitations, and environmental conditions. This capability allows the system to gather data proactively, analyze it effectively, and use the insights gained to make informed decisions. By leveraging self-awareness, a system can dynamically adjust its operational parameters to optimize its own overall performance in real-time [81].

Self-awareness in an IoT-based remote patient monitoring system refers to the system's ability to autonomously perceive, interpret, and respond to changing conditions according to the patient's health status, activities, and the surrounding environment. Such a capability contributes to efficient resource management, ensuring that various resources are utilized optimally to maintain the system performance and improve patient care [82].

This chapter proposes a self-aware model for managing the resources of a remote health monitoring system effectively. The model integrates the *Observe*, *Decide*, *Act* (ODA) awareness model and introduces multiple components distributed across the IoT architecture layers. These components are responsible for collecting and processing patient data, taking into account the patient's health, activity, and environment. They also update the thresholds of warning scores and adjust the sensing devices as needed. The primary goal is to efficiently manage energy resources, with extra attention given to the patient's health status when necessary.

4.1 Self-aware IoT-enabled EWS System

The proposed self-aware system consists of a novel framework developed for the local processing of Early Warning Score (EWS) systems outside of hospital settings, integrating the concept of ODA self-awareness model into an IoT-based health monitoring architecture. As shown in Figure 15, the core functions of the edge layer are segmented into five distinct components: *Biosignal Pre-processing*, *Situation Awareness*, *Self-awareness Core*, *Attention*, and *Reconfiguration*. While the sensor layer provides data for the *Observe* part and acts as a receptor for the reconfiguration in the *Act* part, the edge layer acts like a core for the *Decide* part, where all awareness components are acting. Figure 15 shows the *Observe*, *Decide*, and *Act* components marked respectively via red, blue, and green dotted lines.

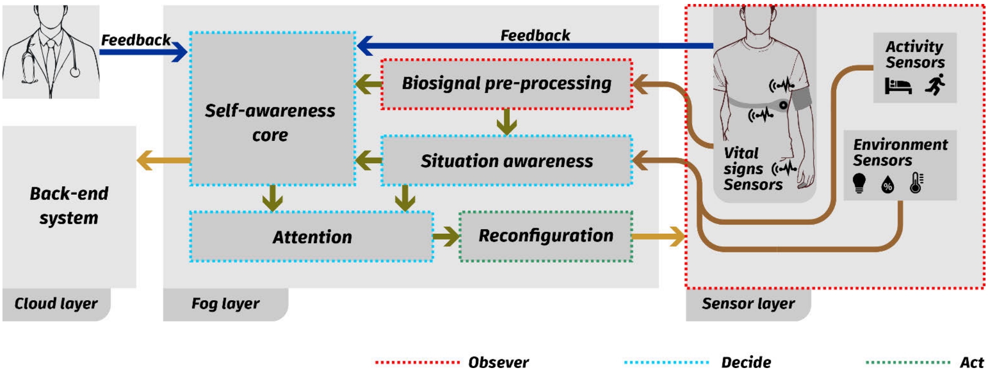

Figure 15. The architecture of the self-awareness model following the ODA model, represented within the IoT-based health monitoring system.

4.1.1 Biosignal Pre-processing

The *Biosignal Pre-processing* component collects raw data from various sensor nodes. It involves two main stages: signal enhancement and preparation, followed by medical parameter extraction. The first stage improves signal quality and prepares it for analysis. This includes noise reduction using techniques like filtering or averaging, artifact removal, baseline correction using polynomial fitting or high-pass filtering, normalization to scale the signal to a standard range, and segmentation to divide it into relevant portions. The second stage extracts clinical information from the cleaned signal. Feature extraction identifies key characteristics in time, frequency, and time-frequency domains. Peak detection algorithms locate important points in the signal. Specific parameters are then calculated: heart rate through R-R interval analysis in ECG or peak-to-peak interval in PPG; respiration rate via chest movement analysis, PPG, or inhale-exhale airflow; blood oxygen saturation (SpO_2) using the ratio of IR and red PPG signals; and blood pressure through the pulse wave analysis. The choice of methods depends on the specific signal, desired outcomes, and available resources. Once refined and processed, the vital signs are sent to the *Situation Awareness* component for further analysis and decision-making.

4.1.2 Situation Awareness

Situation Awareness is a component that collects and interprets data from sensors to understand a patient's state and environment. As shown in Figure 16, this component consists of two main units: *Analysis* and *Ambiguity Resolution*. The *Analysis* unit includes activity and environment analysis units, which use decision trees to determine the patient's situation. The activity analysis categorizes the patient's movements into postures such as sleeping, resting, walking, jogging, and running based on acceleration data. The environment analysis classifies the

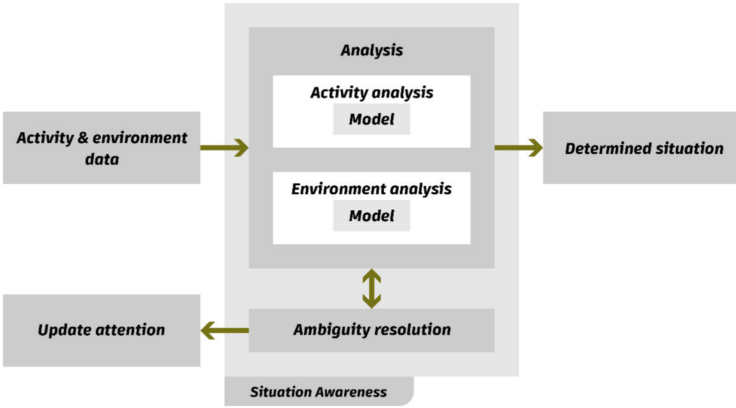

Figure 16. The block diagram of the *Situation Awareness* component.

surrounding context into categories like indoor/outdoor or day/night using data from temperature, humidity, and light sensors. The *Ambiguity Resolution* unit manages uncertainty and optimizes system resources. When the *Analysis* unit's results are ambiguous, it requests new information sources to clarify the situation. For example, if the temperature sensor is insufficient to determine whether the patient is indoors or outdoors, it might activate a light sensor for additional data. If redundancy is detected, this unit can request the removal of unnecessary resources to conserve energy. The *Situation Awareness* component interacts with other parts of the system by providing the patient's situation to the core component and updating the *Attention* component if there's uncertainty in the assessment.

4.1.3 Self-awareness Core

The *Self-awareness Core* acts as the central analytic element of the system, tasked with modifying the system's settings (like energy usage and bandwidth) and abstracting patient data for the back-end services. It processes vital signs and contextual information to generate an improved, context-sensitive, personalized scoring model known as Self-aware EWS. This core also evaluates the reliability of incoming data and implements corrective strategies to address any inconsistencies, as depicted in Figure 17. It encompasses two primary units: the *Analysis* unit and the *Self-aware EWS* Unit.

The *Analysis* unit uses semantic analysis and modeling based on patient activity and environmental contexts. It employs abstraction and disambiguation techniques to yield definitive information for the models and back-end services. *Abstraction* translates medical and state data into meaningful interpretations, such as understanding a "low" level emergency for a patient with a 140 beats per minute heart rate while running outdoors. *Disambiguation*, meanwhile, aims to clarify

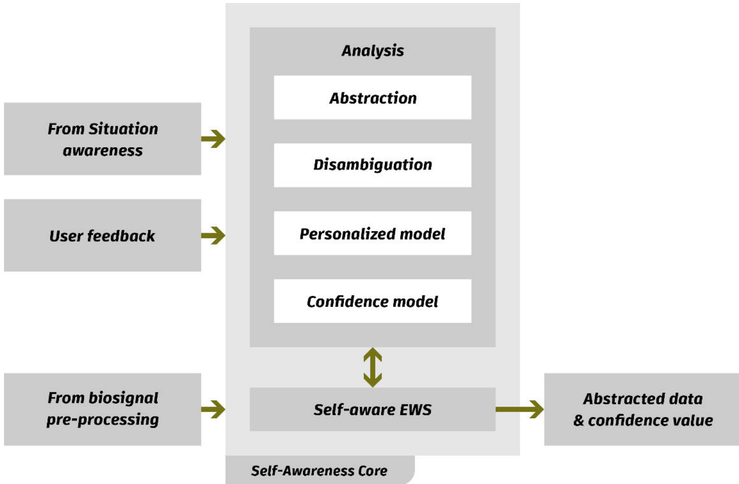

Figure 17. The block diagram of the *Self-awareness Core* component.

inconsistencies when divergent values for the same condition appear. This unit constructs two models with preset metadata through rule-based and decision-tree classification methods. The *Personalized Model* is adapted to the patient's static parameters like age, BMI, and gender, and it evolves with feedback from both patients and healthcare professionals during the monitoring phase. The *Confidence Model* gauges the system's reliability by evaluating medical parameter aspects like natural and variation ranges and event interdependencies.

By leveraging the *Analysis* unit's findings concerning the patient's situation and a rule-based algorithm, the *Self-aware EWS Core* recalibrates the conventional EWS to reflect individual and environmental factors better. Consequently, it propounds a new measure by modifying the threshold values. Ultimately, the refined data (including the adjusted EWS and patient condition), along with confidence levels and directives based on the outcomes, are communicated to the back-end system and the *Attention* component. Notably, conveying the confidence level alongside the score and additional data significantly enriches the accuracy of the system and health assessments. For instance, acknowledging low confidence in an evaluation due to incomprehensive or unreliable data prompts users to consider the uncertainty. This aspect is particularly vital when a high score with low confidence might suggest a follow-up check rather than immediate emergency intervention, thereby preventing potential misjudgments.

4.1.4 Attention

The *Attention* component adjusts monitoring settings dynamically to optimize system performance, along with the reliability and quality of sensory data. It

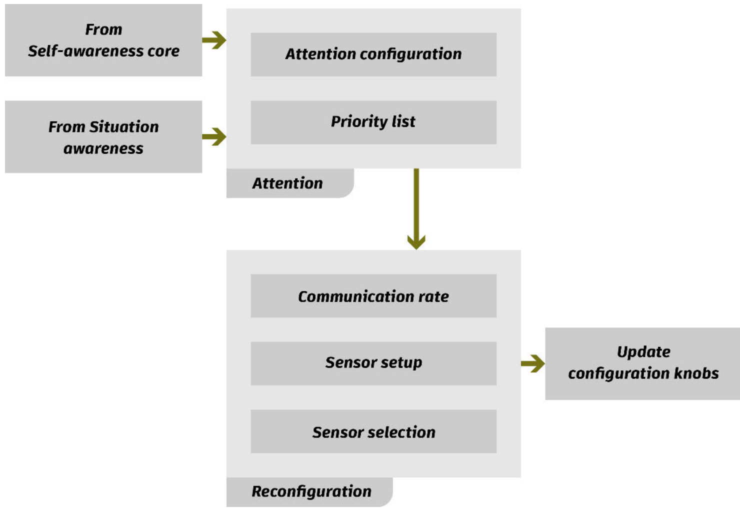

Figure 18. The block diagram of the *Attention* and *Reconfiguration* components.

gathers insights on the patient's condition and environmental context from the *Self-awareness Core* and the *Situation Awareness* components, determining the best configuration for achieving high efficiency and reliability. Instructions are then sent to the *Reconfiguration* component to modify the sensor network's settings accordingly. As depicted in Figure 18, the *Attention* component consists of two primary elements: the *Attention configuration* and the *Priority list*. The former decides which parameters (e.g., sensors) need monitoring and their frequency, while the latter maintains a hierarchy of priorities and resolves conflicts when resources are too limited to meet all attention demands. In this instance, it prioritizes certain requirements over others based on their importance.

In this self-aware EWS model, the *Attention* component is guided mainly by the patient's emergency level, followed by the patient's activity, and finally, the environmental context. Thus, in critical health emergencies, the unit diverts more resources toward patient monitoring. Conversely, in more stable conditions, it shifts focus to other areas where system attributes, like energy efficiency, can be enhanced.

4.1.5 Reconfiguration

The *Reconfiguration* component dynamically adjusts the sensor network based on priority values received from the *Attention* component. This process involves translating the priorities into specific configurations for the sensor network, which has various predefined states. Each state in the sensor network is characterized by a set of parameters that define its behavior and performance. Illustrated in Figure 18, the configuration of each sensor network state is defined by factors such as the communication rate, sensor configuration settings, and the choice of sensors. The communication rate determines how frequently the sensors transmit data to the system. The sensor configuration setup includes settings such as sampling frequency. This setting controls how often the sensors collect data, impacting the accuracy and detail of the information gathered. The sensor selection parameter determines which sensors are active and collecting data and which are in sleep mode to conserve energy. Upon receiving priority values from the *Attention* component, the *Reconfiguration* component maps them to the most appropriate sensor network state and then generates commands that the sensor network can understand and execute to update its configuration. This is the final process that allows the system to dynamically adapt its sensor network to changing priorities and conditions, optimizing resource usage and data collection based on current needs.

4.2 System in Practice

The performance of the proposed self-aware solution for managing the resources of a remote patient monitoring system is evaluated through the development of a reconfigurable sensor network and its associated edge service. The system gathers medical, activity, and environmental data utilizing a set of sensors. By analyzing both patient activities and environmental conditions, the system gains a comprehensive understanding of the situation, allowing it to adjust Early Warning Score thresholds. These updated scores enable the system to modify its state, resulting in reduced energy usage in the body-worn sensor network.

The body area sensor network integrates multiple medical sensors to monitor vital signs and patient activities. A SpO_2 finger grip sensor measures blood oxygen saturation and heart rate, while an airflow sensor tracks respiration rate. A pressure sensor together with an arm cuff measures the blood pressure. A 3D accelerometer records patient activity, and a temperature sensor measures body temperature. To provide environmental context, additional sensors monitor ambient temperature and light levels. The system's hardware is centered around a microcontroller unit (MCU) that collects and processes signals from all sensors, decides on the situation, and controls operational states. Data transmission is handled by a Bluetooth Low Energy RF module, which operates in three power states: sleep, standby, and transmission. This module sends data to an Android smartphone, acting as an edge device.

The Early Warning Score (EWS) system, ranging from 0 to 6, forms the basis of patient health assessment in this adaptive monitoring approach. The system recognizes five activity states (sleeping, resting, walking, jogging, and running) using an accelerometer sensor and adjusts EWS values accordingly. This ensures that natural variations in vital signs due to physical activity are accounted for in health evaluations. Environmental factors are also considered, with conditions classified as day/night and indoor/outdoor based on data from temperature and

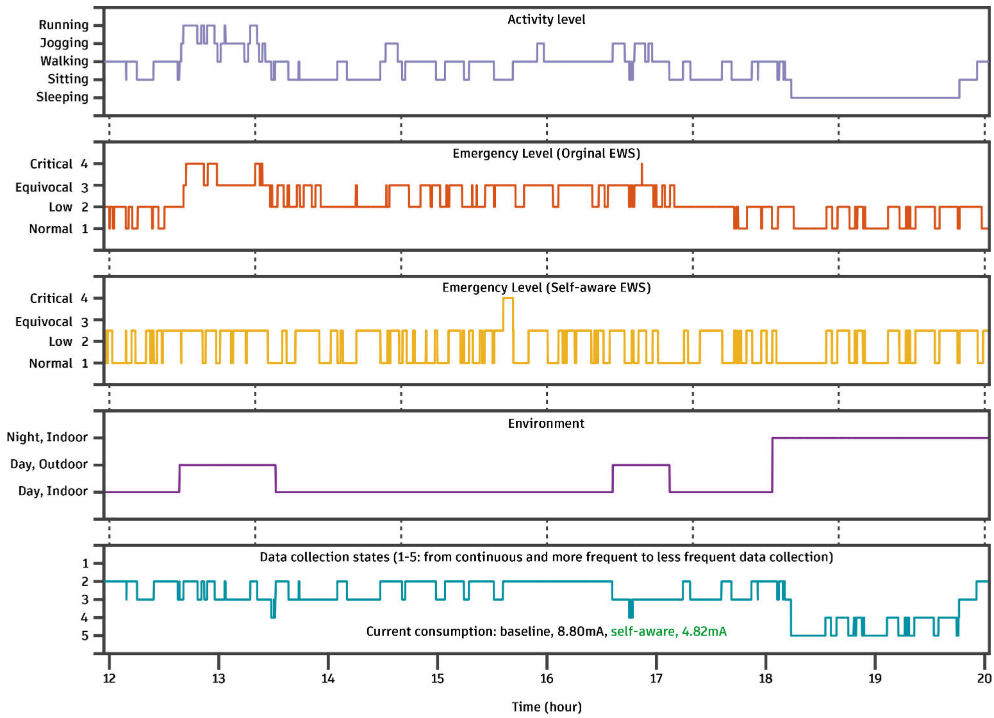

Figure 19. The overview of the self-awareness solution performance in practice.

light sensors, the system clock, and the edge device geolocation services. To balance data accuracy and power efficiency, the sensor node employs five working configurations with varying power consumption profiles. These are based on signal recording continuity and data sampling frequency. A lookup table correlates the patient's health status score with the appropriate monitoring intensity, allowing for more frequent and continuous data collection when health scores are high and less frequent collection when scores are low. This comprehensive approach integrates adaptive scoring, activity recognition, and environmental awareness to achieve accurate health assessments while optimizing resource use.

The proposed system underwent an 8-hour evaluation to assess its performance and efficacy. The results of this test are visually represented in Figure 19, which illustrates the dynamic changes in patient state and environmental conditions over time. This figure also demonstrates how the system autonomously adjusted its operational states in response to these changes, exhibiting its self-aware capabilities. A key outcome of this adaptive behavior is a significant reduction in energy consumption, with the system achieving a 50% decrease compared to a non-adaptive approach. This substantial energy saving highlights the effectiveness of the self-aware resource management strategy. Paper *III* provides the details of the system's configuration profiles and the lookup table that guides its decision-making process. These elements form the core of the system's ability to optimize its performance based on real-time conditions.

4.3 Summary

This chapter introduced a new framework for a self-aware health monitoring system based on the Internet of Things (IoT). This system intelligently updates the medical Early Warning Score system (EWS) to make it usable outside of hospital settings. The proposed architecture, inspired by the ODA awareness model, used various components, including pre-processing, situation awareness, self-awareness, attention, and reconfiguration, to smartly adjust the sensing device workflow based on data collected from the patient, the device itself, and the surrounding environment. A real implementation of the proposed solution demonstrated that the system can reduce the resource utilization of the sensing device during the patient's daily activities while supporting the importance of the patient's health.

5 Resource Management Through Context-awareness

In healthcare Internet of Things (IoT) applications, optimal resource management requires a delicate balance between the system's technical capabilities and the data it generates. Traditionally, these aspects have been managed independently, with system-driven optimizations focusing on hardware and network efficiency and data-driven optimizations prioritizing information extraction and analysis. While this decoupled approach might lead to local improvements within each area, it fails to capture the full potential of the system. Prioritizing system-driven optimization by reducing the frequency of data collection may decrease the power consumption of a wearable health monitor, which negatively impacts the effectiveness of data-driven strategies. Conversely, focusing solely on data-driven optimizations may result in increased energy usage and strain on system resources.

The key lies in a synergistic coupling of these two aspects. System-driven optimizations can be utilized by analyzing the data collected by the system. Understanding patients' activity through data allows for targeted power-saving measures during low-activity periods without compromising data collection. This approach creates a feedback loop, where system optimizations enhance data quality, and the rich data guides further system improvements.

This chapter's approach considers the accuracy of data as a resource in the data-driven aspect and the energy source as a resource from the system-driven aspect, opting for synergic coupling to optimize both aspects. This integrated approach to resource management in healthcare IoT allows for the development of intelligent systems that adapt to patient needs and health conditions, maximizing both system efficiency and the value extracted from the data.

With this approach, the current chapter describes an edge-computing architecture and a reconfigurable sensor node that utilizes this coupling method for resource management of an EWS-based remote health monitoring system in out-of-hospital settings. Here, edge computing empowers the health monitoring system to be more responsive, efficient, and secure. The edge computing architecture places the computing resource closer to the data source, where the edge devices can process data, extract features, analyze vitals, and decide on the correct resource optimization action locally.

Within the proposed solution, the error/noise resiliency of feature extraction

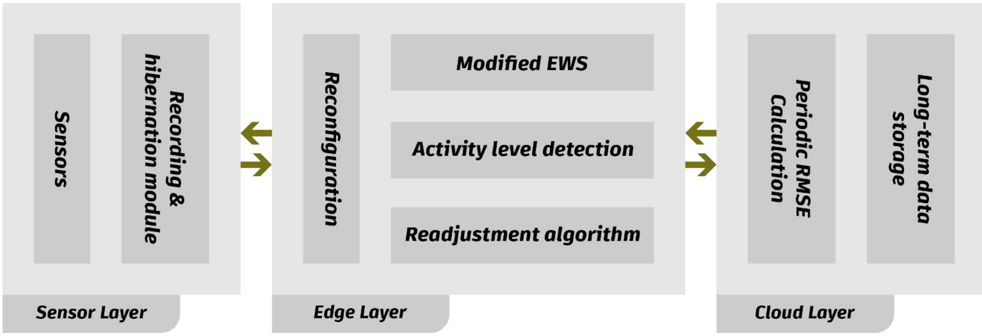

Figure 20. The three-layer IoT architecture of the proposed system.

in biosignals is assessed under varying levels of sensing energy consumption and patient activity. An optimization problem is formulated to minimize the long-term energy consumption of a sensor node while achieving a target accuracy for the extracted parameters. Finally, a runtime control algorithm state machine is developed and resides at the edge layer, enabling real-time adaptation of sensing parameters based on patient states.

5.1 System Architecture

The proposed system utilizes a three-layer IoT architecture to enable health monitoring. As illustrated in Figure 20, the first layer, known as the sensing layer, consists of reconfigurable sensing devices that capture the patient's medical and activity data. This information is then transmitted to edge devices located in the edge layer. These devices perform analysis services on the patient's condition and on the overall system status to determine the best configuration for the sensors. Thereafter, they relay new configuration instructions to the sensors and transmit the combined patient data to the cloud layer. The cloud layer is a storage for long-term patient data, hosting the information in a database for further examination. Furthermore, the cloud regularly updates the baseline parameters utilized by the edge controller based on the accumulated data, ensuring continuous optimization of the system.

5.1.1 Reconfigurable Sensor Node

The edge layer's local control feature is enabled by a reconfigurable sensor node. This allows for dynamic adjustments of sensing fidelity and hibernate period. The sensor node acts as a remotely configurable data collector, receiving instructions from the edge for its new task during each iteration. It functions as a wireless activity and medical vital signs monitor, utilizing a PPG sensor to capture heart rate, respiration rate, and blood oxygen saturation, a temperature sensor to measure

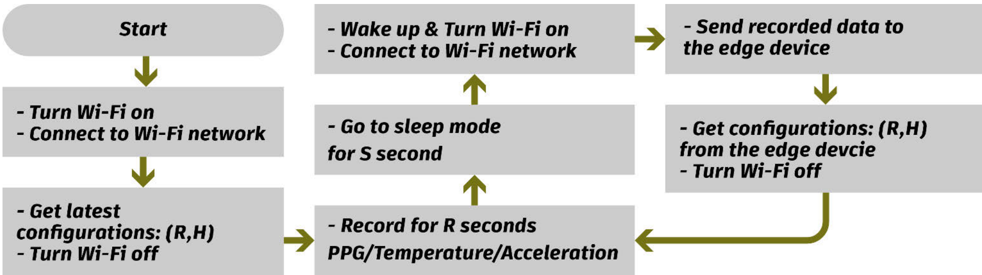

Figure 21. The flowchart of the functions within the sensing device.

skin temperature, and a 3D accelerometer to monitor the patient's activities. Data collected by these sensors is stored locally by a microcontroller and then transferred to the edge device using a low-power Wi-Fi module. After transferring the data, the sensor node enters hibernate mode for a time interval specified in the configuration. Upon completion of the hibernation duration, the sensor node reactivates and starts recording based on the most recent instructions. A web service within the edge device determines the new configuration string based on the patient's current state when it receives, stores, and analyzes the data. A flowchart in Figure 21 outlines further details of the sensor device's functions. The configuration command fine-tunes the sensor node's power consumption during data recording. It defines the recording and sleep durations, turns off unnecessary components like the RF module, and optimizes the power usage of the PPG sensor LEDs to achieve the best balance between data quality and battery life.

5.1.2 Context-Aware Resource Management

To optimize resource usage, the edge layer implements a resource management service with a set of algorithms. These algorithms monitor the patient's state (e.g., sleeping, running) to adjust the accuracy and duration of data collection dynamically. This context-aware approach tailors the data acquisition process to the patient's current activity. For instance, since motion noise is significantly lower during sleep, the sensor node can use less energy to achieve the same accuracy level compared to when the patient is active. This intelligent control based on patient context (like activity type) can significantly reduce energy consumption.

Figure 22 provides an overview of the proposed edge-assisted resource management architecture for this application. The key component is the context-aware cognitive engine residing at the edge layer. This engine analyzes the patient's state and optimizes the parameters for sensor operation (including periods of low-power hibernation) to maximize the continuity of the system's operation while ensuring acceptable accuracy from the PPG signal. This process consists of two interconnected manageable options: sensing accuracy and sensing duration.

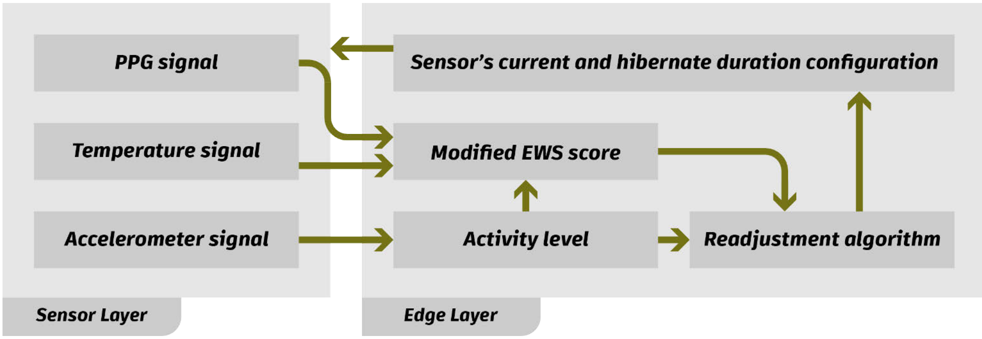

Figure 22. The block diagram of the edge-assisted control architecture.

5.1.3 Sensing Accuracy

The resource management edge control uses RMSE (Root Mean Square Error) to assess how well the sensor readings match the reference values in different contexts. It compares the sensor's reading for a specific feature (heart rate, respiration rate, SpO_2) with the corresponding value from the reference source (ECG, airflow sensor, accurate PPG). This difference essentially shows how far off the sensor's reading is from the actual value. The RMSE of the calculated features is a function of the current consumption level of the PPG sensor U and X, the subject's activity state. The type of activity is divided into five different categories:
$X \in \{\text{Sleeping, Sitting, Walking, Jogging, Running}\}$.

For a range of the PPG sensor input current, the total RMSE would be the weighted sum of the RMSE of the three individual features:

$$\epsilon(U, X) = \{\gamma_1\epsilon_1(U, X) + \gamma_2\epsilon_2(U, X) + \gamma_3\epsilon_3(U, X)\} \tag{1}$$

The RMSE is determined by taking the square of the difference between each pair of the actual value and the measured feature to obtain a positive number. Subsequently, all the squared values of the samples are summed up, and the sum is divided by the number of samples. Finally, the square root of the division is calculated:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_{ref} - S_{mes})^2} \tag{2}$$

Here, S_{ref} is the reference feature sample and S_{mes} is the measured feature sample.

Given that the features do not exhibit even accuracy magnitudes in their response to changes in U and X, the coefficients $\gamma_1, \gamma_2, \gamma_3$ are utilized to normalize the

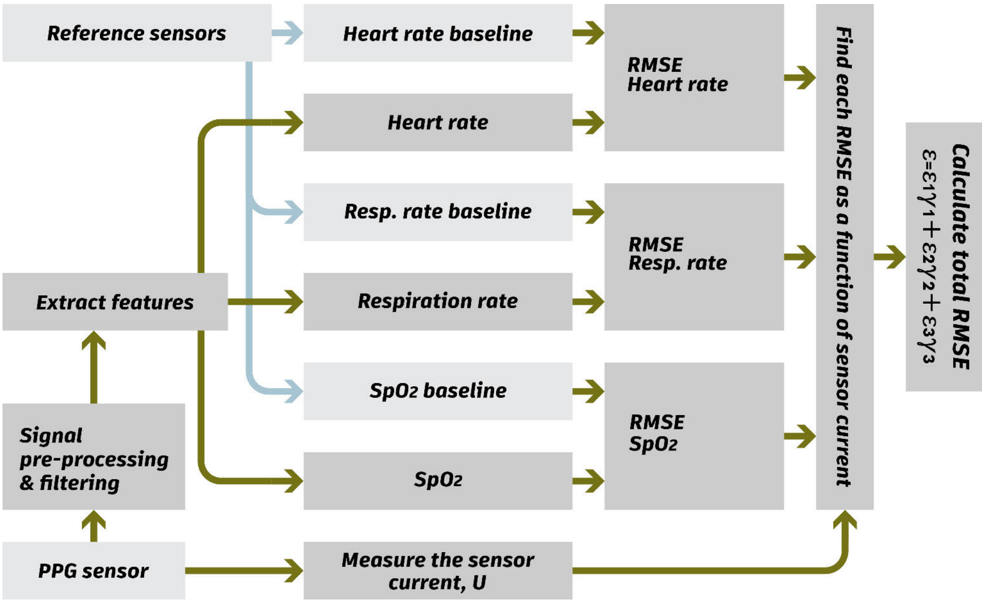

Figure 23. The block diagram of the RMSE calculation.

importance of each feature so that $0 < \gamma_1 \leq \gamma_2 \leq \gamma_3 < 1$. Figure 23 illustrates the block diagram for the RMSE calculation.

The sensor's energy consumption $E(U, X)$ is dependent on the patient's activity and the sensor's current level, and we aim to determine the best sensor setting for each activity type while ensuring that error measurements $\epsilon(U, X)$ meet a specified threshold τ. This involves minimizing $E(U, X)$ while satisfying $\epsilon(U, X) \leq \tau$.

The problem can be formulated as a convex optimization problem with a Lagrangian function $\mathcal{L}(U, \lambda)$ defined as

$$\mathcal{L}(U, \lambda) = E(U, X) + \lambda(\epsilon(U, X) - \tau) \tag{3}$$

where λ is a trade-off parameter representing the importance of accuracy and energy cost. By taking the derivative of the Lagrangian function with respect to the sensor's current level, we aim to find the optimal value of U for each activity level X to minimize the total cost.

$$\frac{\partial E(U, X)}{\partial U} + \lambda \frac{\partial \epsilon(U, X)}{\partial U} = 0 \tag{4}$$

Under the assumption of a linear relationship between energy consumption and the sensor's current level, the derivative of $E(U, X)$ with respect to U is a constant a_U, while the derivative of $\epsilon(U, X)$ with respect to U is a constant b_U considering the total RMSE $\epsilon(U, X)$ be linear to the current level U. The Lagrangian multiplier can be calculated as $\lambda = -\frac{a_U}{b_U}$, and solving this optimization problem will yield

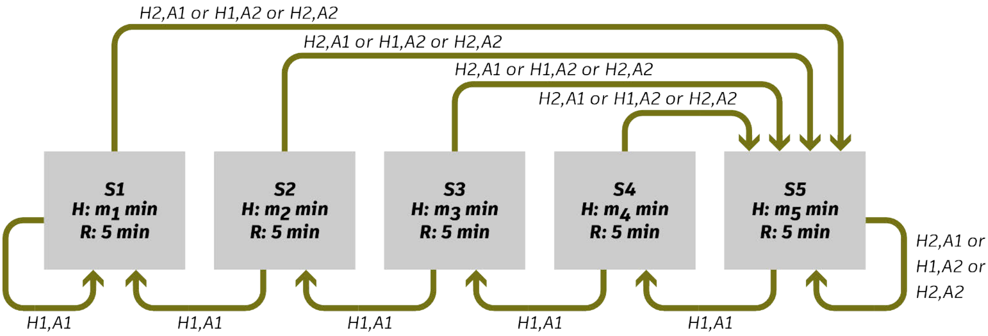

Figure 24. Sensing device readjustment state machine.

the optimal current level U^*. This optimized solution guides the sensing device in establishing the ideal current level for monitoring.

5.1.4 Sensing Duration

The context-aware resource management system utilizes a state machine to dynamically adjust both sensing and hibernation duration based on the patient's health and activity level. This state machine, shown in Figure 24, comprises five states, with transitions triggered by various combinations of four distinct contexts. Two contexts (H1 and H2) are related to the patient's health, as determined by the Early Warning Score (EWS). H1 represents a normal health state with EWS scores below 3, while H2 indicates an abnormal condition with EWS scores at or above 3. Similarly, the other two contexts (A1 and A2) are based on the patient's activity level. A1 signifies low-intensity activities like sleeping and sitting, while A2 encompasses high-activity contexts such as walking, jogging, and running.

The state machine starts in state S1, which has the longest hibernation time, allowing for efficient power usage. This state persists as long as no concerning events occur. However, if the system detects abnormal or intense activity, it immediately transitions to state S5, characterized by continuous monitoring with zero hibernation. This ensures close observation during potential health concerns. State S5 remains active until the abnormal activity subsides.

Upon returning to normal conditions, the system gradually increases the hibernation time through a series of intermediate states (S4 to S1). Importantly, the system bypasses these intermediate states to avoid unnecessary delays in health reassessment if the abnormality reoccurs. This design prioritizes rapid detection of potential health issues while maximizing energy conservation during stable periods.

Figure 25 shows the combination of sensing accuracy and sensing duration determination processes for creating sensing device configuration instructions.

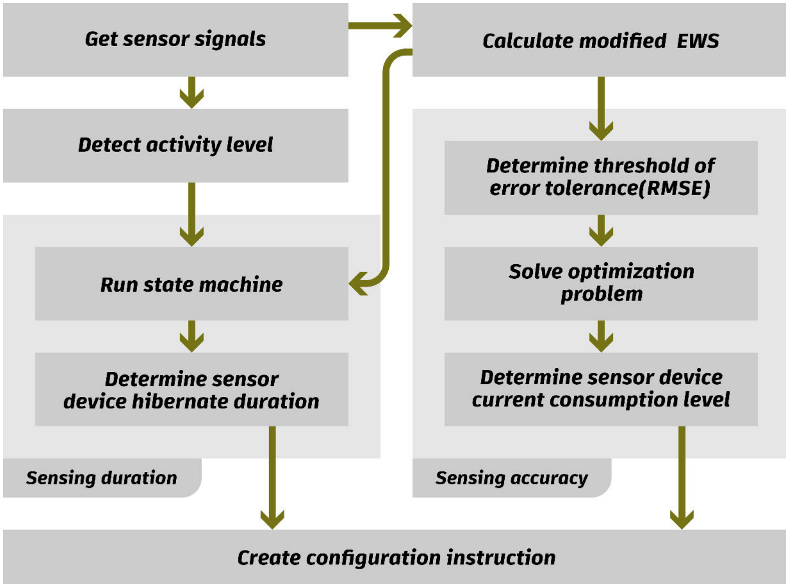

Figure 25. The block diagram of combined processes of sensing accuracy and sensing duration determination for creating configuration instruction.

5.1.5 System in Practice

The performance of the proposed context-aware resource management solution for an IoT-based health monitoring system is studied using a synergistic approach that considers both data- and system-driven aspects.

The evaluation began with the design of an accurate, non-resource-limited data collection system. This system is engineered to collect reference signals accurately, ensuring that all vital signs were captured across different activity states. A total of 150 sets of data were collected, monitoring six healthy subjects engaging in five different activities (sleeping, sitting, walking, jogging, and running) and utilizing five levels of PPG sensor current consumption.

Following this, a reconfigurable sensor node and its corresponding edge services were designed with the specified parameters provided earlier to evaluate the performance of the proposed solution. Several scenarios were considered for the hibernation duration and the effect of each scenario on power consumption and missing events—a proposed parameter for selecting the optimal hibernation duration setting. Five different states were also defined, representing the sensor node power consumption profiles.

The developed system monitored a healthy subject for 24 hours to evaluate its performance and efficacy. The results of this test are presented in Figure 26, showing the patient's activity level, the calculated modified EWS, the total RMSE expected regarding the patient's activity, the device states, and the device power consumption

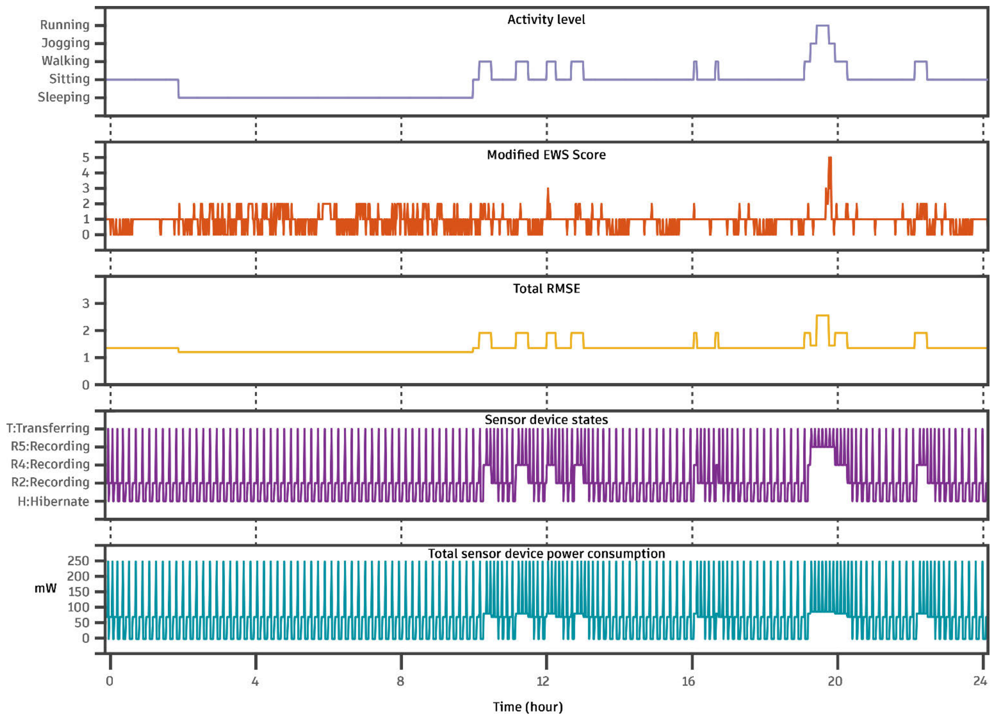

Figure 26. The overview of the context-awareness solution performance in practice.

during the monitoring. The evaluation showed that the edge controller could save 49% of the battery power, demonstrating the efficacy of the proposed edge-assisted intelligent control scheme. Paper *I* provides the details of the sensor node design, specifications of the reference data collection system, description of the hibernation scenarios and power consumption profiles, as well as the calculated RMSEs.

5.2 Summary

This chapter presented a novel context-aware resource management approach in remote health monitoring systems. It demonstrated a coupled solution for both data-driven and system-driven aspects, considering data accuracy as a data-driven resource and energy as a system-driven resource. The proposed solution adjusts itself to the most energy-efficient setting while retaining a desirable level of accuracy, considering patient medical and activity states. The chapter detailed the implementation of the optimization method and explored how the runtime algorithm functions on a reconfigurable sensor node. The significance of the proposed method was evaluated by assessing the accuracy of data collection and the implementation of the sensing and edge device. It proved that the solution is potent to reduce power consumption by half while preserving a minimum level of quality for the collected data.

6 Resource Management Through Goal Management

The goal of a system is the desired outcome that it aims to achieve. In the context of resource management, this goal can be described by examining the system's *inputs*, *outputs*, and *processes*. *Inputs* are the resources necessary for the system to function, while *outputs* are the results expected from the system. *Processes*, on the other hand, encompass the activities the system undertakes to convert *inputs* into *outputs*. These activities can be further broken down into monitoring, decision-making, and reconfiguration, and can be modeled using the *Observe*, *Decide*, *Act* (ODA) framework, which was introduced in Chapter 3 and has been utilized in earlier dynamic resource management solutions. Similar to the other solutions discussed in this thesis, this chapter also presents a solution that uses the ODA model to optimize resource usage in a remote health monitoring system from a goal management perspective.

On a small scale, a system might provide just a single service, thereby pursuing only one goal. However, on a larger scale, a system can simultaneously strive to achieve multiple goals. In a multi-goal system, goals are classified based on their interrelations into three types: independent, compatible, or conflicting. The fulfillment of an independent goal neither affects nor is affected by the fulfillment of other goals. In contrast, compatible goals can be achieved together, where the success in one enhances the likelihood of attaining the other. Conflicting goals present the most significant challenges, as attaining one goal might reduce the probability of fulfilling another, affect the quality of other goals, substantially increase the costs associated with achieving other goals, or even hinder the fulfillment of another goal altogether. While the primary focus in managing goals in multi-goal systems with unlimited resources often centers on conflicting goals, systems constrained by limited resources must also consider the management of independent and compatible goals. This consideration is essential because the finite resource pool can significantly impact the quality of achievement across all goals.

In IoT systems, goal management involves the complex task of handling multiple goals, which may sometimes conflict or require prioritization due to limited resources. The process of real-time prioritization based on observations and conditions, allowing the system to adapt to changing requirements and resource availability at runtime is called dynamic goal management. This approach

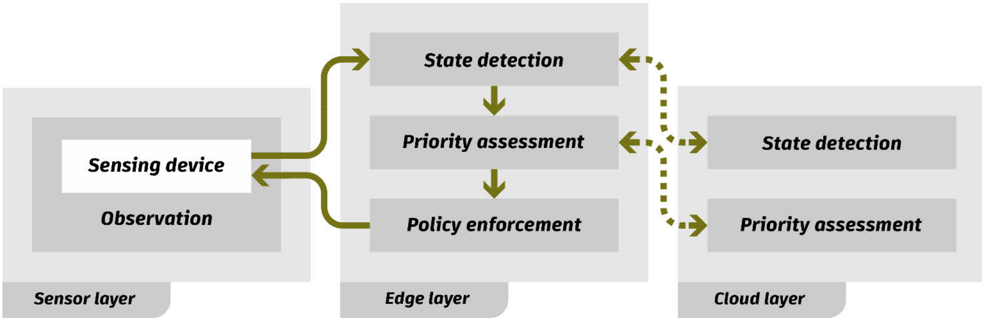

Figure 27. The architecture of the goal management model represented within the IoT-enabled health monitoring system.

emphasizes the coordination of overlapping and conflicting goals to ensure optimal system performance and Quality of Experience (QoE) across different IoT layers (sensing, edge, cloud).

Regarding the limited resources, power management is a significant challenge for wearable sensors in IoT-based remote patient monitoring systems. These sensors need to preserve battery life while ensuring accurate data collection, creating a conflicting goal situation. Previous solutions have included using sensors in low-power modes, reducing wireless transmission strength, and recording data periodically. However, these approaches have their own drawbacks. Lowering sensor power or transmission signal strength can result in inaccurate data or connection issues, and periodic recording may miss critical health changes.

An optimal solution would involve dynamic goal management, intelligently combining these methods, and prioritizing goals based on the specific situation. This smart goal management system would benefit from being aware of its own state and goals. In patient monitoring, goals include providing the maximum amount of medical information possible during emergencies, long battery life, and accurate data collection, with priorities focused on patient health and minimizing the interruption in the monitoring process when the batteries need replacement.

This chapter presents a novel solution for remote patient monitoring that utilizes a dynamic goal management method to achieve these goals. The system takes into account the patient's health, activity level, and sensor battery life to prioritize defined goals and choose the most suitable power management policy. It continuously monitors the situation and dynamically adjusts the policy as needed. The chapter also introduces a remotely reconfigurable sensor node developed to demonstrate this dynamic goal management approach.

6.1 Dynamic Goal Management

As illustrated in Figure 27, the goal management solution is composed of four sections that work together across different layers. The *Observation* module is located on the sensor layer and continually checks the patient's health status and the sensor's condition. If it detects a significant change, it sends a report. The *State Detection* module is situated in the edge layer and receives reports from the *Observation* module. It analyzes the report using the cloud-based patient's health history to determine the patient's current health and activity level. It then sends this information to the *Priority Assessment* module, in the same layer, to evaluate the importance of the monitoring goals. This module considers the patient's cloud-based history of low battery periods to determine which monitoring aspects are most crucial at the moment. The edge layer also contains the *Policy Enforcement* module that selects the most suitable data recording policy based on the priorities set by the previous module. It then sends this chosen policy back to the sensor node, instructing it on how to collect data. Quite similar to other studies, the proposed goal management solution is applied to a sensing device that uses a PPG sensor and a temperature sensor to retrieve vital signs, an IMU sensor to detect subject activities, and an ultra-low-power RF module for wireless communication.

6.1.1 Observation

Within the *Observation* module, the sensing device continuously monitors the patient's health status every R seconds. During each iteration, the device assesses the patient's state by calculating the heart rate using a window of W seconds of PPG signal data and measuring the acceleration and posture data obtained from the IMU sensor. The results of this assessment are then compared with the findings from the previous observation cycle. If a significant change is detected in either metric, the sensor transmits the recorded sample to the edge layer for further evaluation and enters a wait state, expecting to receive instructions regarding the data recording process. On the other hand, if no significant changes are identified, the sensor node enters a deep sleep mode lasting S minutes. When the device wakes from this sleep state, it initiates another loop, recommencing the self-observation process. The observation and recording flowchart is detailed in Figure 28. The "significant change" in heart rate is defined based on the standard healthy heart rate range according to the Early Warning Score (EWS) table. When it comes to activity level, the sensor recognizes five distinct activity types: sleeping, sitting, walking, jogging, and running. The sensor node distinguishes between sleeping and sitting primarily through posture data while employing the amplitude of acceleration to detect the remaining activity categories. Any changes between activity classifications observed in two consecutive monitoring cycles are considered indicative of a major change.

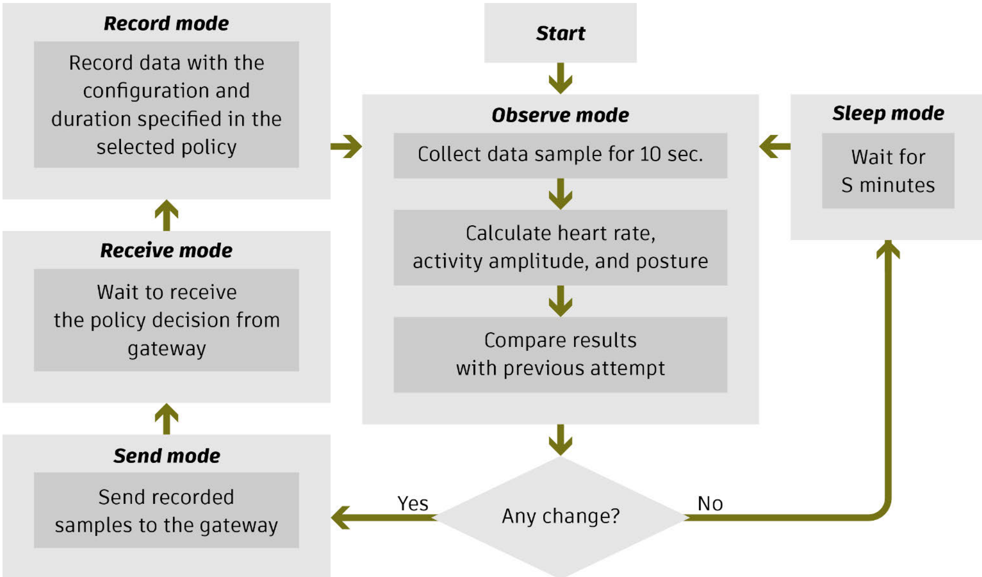

Figure 28. The flowchart of the observation and recording modes within the sensing device.

6.1.2 State Detection

The *State Detection* module, located within the edge layer, receives data directly from the sensing device. The wireless transceiver module of the edge device continuously operates in listening mode, waiting for incoming data samples from the sensor. When a sample is received, the edge device filters and analyzes the data, calculating metrics such as heart rate, respiration rate, and blood oxygen saturation with higher accuracy compared to the sensor node's basic assessments. Additionally, the received data includes the sensor node's battery level and raw signals from the IMU sensors. Similar to the self-observation process on the sensor node, the edge device uses the IMU's acceleration data to classify the patient's activity type and posture, while its gyroscope data helps in further refining posture estimation.

Once all necessary processing is complete, the *State Detection* module generates a report that is transmitted to the *Priority Assessment* module. This report contains information about the patient's health status, including whether they are experiencing any abnormal conditions. Additionally, it relays the patient's current activity level and the remaining battery life of the sensor node. Since blood oxygen saturation is considered a highly sensitive indicator of potential patient deterioration, the *State Detection* module leverages the standard range defined within the Early Warning Score (EWS) table to determine the presence of abnormal health conditions based on this specific parameter.

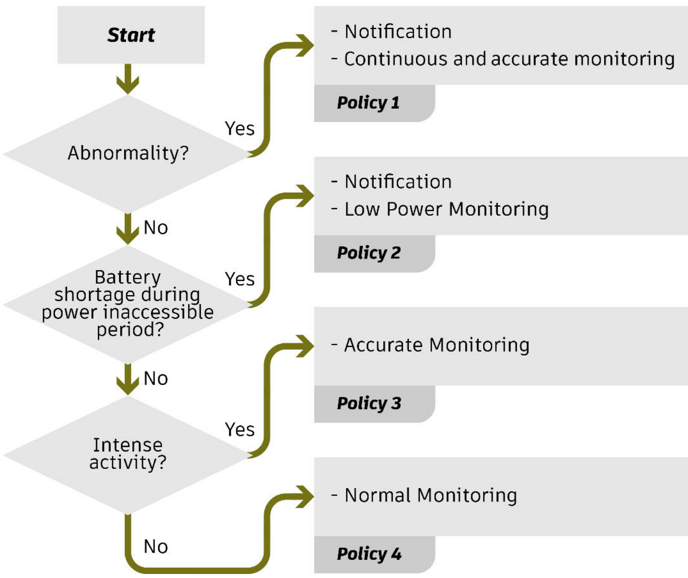

Figure 29. The flowchart of the goals and priority assignment within the edge layer.

6.1.3 Priority Assessment

The *Priority Assessment* module receives information about both the patient's health state and the overall system state. It uses a predetermined hierarchy to prioritize various objectives and select the most efficient data collection policy for the sensor node. In this goal-based monitoring system, the patient's health status is given the highest priority. If an abnormality in the patient's health is detected, the system sends alerts to the patient, their caregivers, and the hospital. All available resources are then allocated to continuous and high-accuracy monitoring to provide up-to-date information to remote healthcare professionals before emergency services arrive.

The next priority is to maintain uninterrupted monitoring whenever possible. The primary cause of interruptions is sensor node battery replacements. Ideally, these replacements should not occur during periods when the patient is unable to change the battery, such as during sleep. The *Priority Assessment* module addresses this by estimating the remaining battery life based on the current level, the active data collection policy, and historical data on the patient's sleep schedule. If the system anticipates a battery failure during the patient's sleep time, it proactively sends a notification prompting the patient to replace the battery before going to sleep. In scenarios where the patient doesn't replace the battery, the system selects a low-power consumption policy for the sensor node to minimize potential interruptions in data collection.

The final priority concerns the accuracy of the collected data. The sensor node should be capable of adjusting its operating mode to compensate for motion artifacts, such as those resulting from high-intensity activities like running. The sensor node can switch to a higher power consumption mode to ensure accurate data collection during these periods. Figure 29 illustrates the flowchart for goal definition and priority assignment.

6.1.4 Policy Enforcement

The system establishes a set of policies that govern how the sensor node operates. These policies determine how the sensor node collects and sends data. A module enforces these policies by translating priority information from higher levels and configuring the sensor node accordingly.

After each data transfer from the sensor layer to the edge layer, the sensor node goes into a waiting state, anticipating instructions on data recording. The edge device then sends the configuration corresponding to the chosen policy back to the sensor node. This configuration effectively guides the sensor node on how to proceed with data collection for the next cycle.

6.2 System in Practice

A sensing node and an edge device were designed to implement the proposed goal-management solution and assess its resource management capabilities. The evaluation process began with presenting the method for identifying the optimal settings for the sensor node. Subsequently, the optimized settings were utilized to assess the system's performance. To determine the optimal settings for the sensor node, 100 different combinations of recording duration (R) and sensor sleep duration (S) were tested, ranging from 1 to 10 minutes for each. In a simulated scenario, a healthy user with a fully charged battery was assumed, and user activities were generated synthetically based on the transition probability matrix for human activities. Random sleep durations of 5 to 8 hours, varying postures, and the probability of activity changes were incorporated into 300 days of simulated data. While choosing the shortest duration for the record mode and the longest duration for the sleep mode results in the best energy consumption reduction, a long sleep mode duration causes the system to lose some of the activity states or posture change events. Therefore, a parameter called "missing events" was introduced to limit the increase in sleep duration, representing the number of events that should have been monitored but were missed due to extended sleep periods. Running 30000 tests (300 days in 100 combinations) revealed that a configuration of 2 minutes for both recording and sleep durations yielded the optimal balance between power reduction and event capture. Compared to the baseline system, power consumption was reduced by 44%, and missed events were reduced by 90%. Figure 30 describes a 24-hour experiment showing the distribution of missing events and the effect of

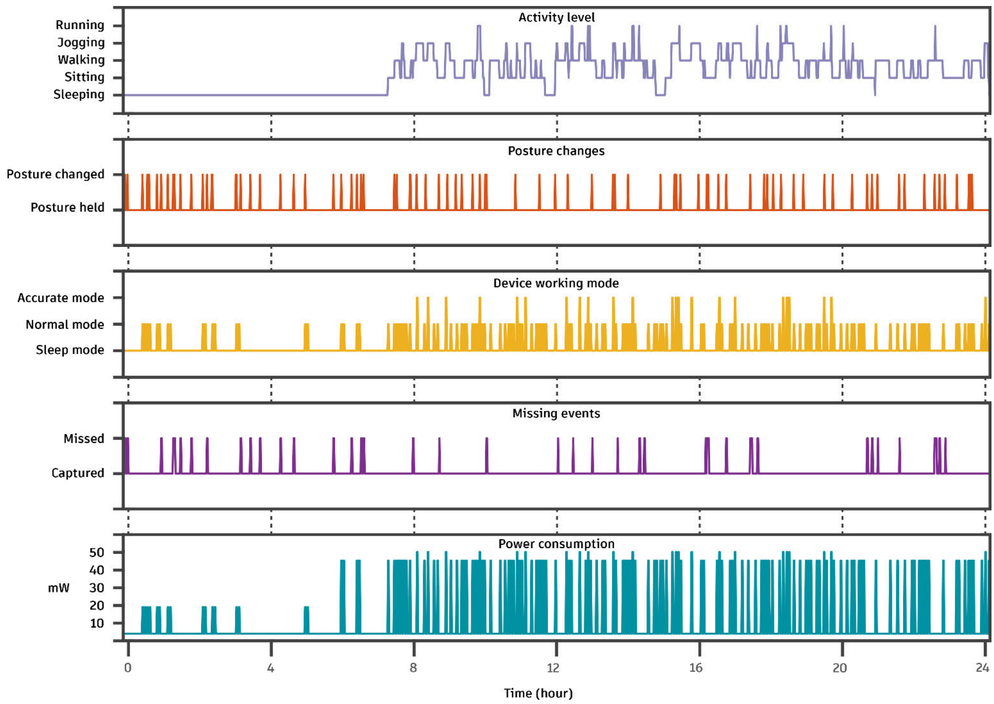

Figure 30. The overview of the goal management solution performance in practice.

daily activity and posture changes on the device modes. With the selected settings, the sensor node could operate for approximately 62 hours using a CR2032 single-use coin cell or 13 days using a rechargeable Lithium-Polymer battery. The priority assignment algorithm proved effective in preventing data collection interruptions, avoiding potential data loss of 56 hours (equivalent to 0.78% of all collected data) over the 300-day test period.

6.3 Summary

This chapter described a dynamic approach for the resource management of a multi-goal IoT system to provide the best monitoring performance during emergency situations, elongate the battery life, and preserve the accuracy of data collection within a wearable-based remote health monitoring system. The proposed self-aware goal management solution considers the health status of the patient and minimal monitoring interruption as priorities. The system dynamically observes the patient and system status and applies a proper policy on the sensing device configuration. The implementation of the proposed goal management solution exhibited a significant enhancement both in power consumption reduction and interruption prevention.

7 Resource Management Through Dynamic Computation Offloading

In large-scale IoT systems with numerous sensors sending data simultaneously, efficient resource allocation is crucial for effective resource management. This process ensures that the right resources are assigned to the appropriate tasks at the right time, enhancing the chances of completing the entire process on schedule and within budget. As a system grows in size, the dynamics of system resources change. Some resources that were previously easy to manage become more dominant due to the increased number of requests the large-scale system needs to handle. In widely distributed IoT systems that involve an extensive network of interconnected devices, time and processing power are considered notably important resources, highlighting the need for effective resource management.

7.1 Time as a Resource

Similar to the other resources of an IoT-based health monitoring system, time is also a finite resource that needs to be managed efficiently to ensure optimal system performance. Like other resources in such systems, the response time of task completion is limited, its proper allocation is crucial for real-time operations, and mismanagement impacts the Quality of Service (QoS).

In a health monitoring system, response time is defined as the period between the moment when sufficient data is collected for decision-making and the moment when the result is delivered to the end-user. In the context of an IoT-based health monitoring system, the key components contributing to response time are computation time and communication cost. Computation time refers to the duration required to process the collected data and generate actionable results. It is dependent on computation power as another system resource. Communication cost, on the other hand, pertains to the time taken to transmit data between various layers of the IoT architecture, such as the sensor layer, edge layer, and cloud layer. This includes both the time it takes to send raw data from sensors to processing units and the time it takes to send the processed results back to the user's device or another endpoint.

The solutions proposed earlier for resource management have primarily addressed the interactions between the sensor, edge device, and cloud as a singular loop, operating under the assumption that the system architecture consists of just one sensor. This approach simplifies the design and implementation of response time resource management strategies, focusing on the direct transmissions for a single data stream. However, this simplification falls short when scaling up to real-world scenarios where multiple sensors are often deployed concurrently to monitor and collect data from various sources. The presence of multiple sensors can significantly increase the volume of data that needs to be processed and transmitted, leading to potential bottlenecks at various points in the system, such as at the edge layer or during data transmission to the cloud.

Such an approach introduces the primary influencing factors of communication costs in remote monitoring systems: the size of the data being transmitted and the number of transmissions required. Data size is a significant consideration since the raw data collected by sensors is typically volumetric, leading to substantial amounts of data needing to be sent to higher layers for processing. Once processed, the resultant data is often much smaller, but the initial transmission of raw data can impose considerable delays. The number of transmissions also plays a critical role since a vast number of sensors are often deployed to collect health-related data continuously. Computation tasks involve multiple rounds of data transmission between the sensors, edge, and cloud layers. Even if the total volume of data doesn't markedly increase, the frequency of these transmissions contributes significantly to the communication cost, which can negate the advantages of faster computational processing at higher layers.

7.2 Computation Power as a Resource

Computation power is the capacity of a system to process data and perform calculations. In an IoT-based remote monitoring system, computation power is a critical resource that needs to be effectively managed to ensure efficient operation, timely data processing, and optimized performance. Data processing is the primary role of computation power in processing the raw data collected by IoT sensors. This involves filtering noise, data analysis, and often running complex algorithms or machine learning models to extract useful insights. As a result of data processing, the computation power resource is also consumed in decision-making.

It is evident that computation power and response time are closely interrelated, with an increase in computation power leading to a decrease in response time. Given the varying levels of computational capability within an IoT architecture, an effective strategy for managing response time involves distributing processing tasks across different layers. However, this strategy necessitates consideration of associated communication costs. Computation offloading is an approach for transferring computational tasks from resource-constrained devices, such as IoT sensors or mobile devices, to more powerful external computing resources like edge devices or cloud servers. By employing dynamic and intelligent resource placement and resource scheduling, this strategy can optimize performance, enhance the efficiency of resource-limited devices, and minimize communication costs.

A dynamic computation offloading engine is expected to make three key decisions correctly: the ideal destination for offloading tasks, the timing of offloading, and the portion of the task that needs to be offloaded. This first decision hinges on several factors, including the desired outcome (minimizing response time, saving energy, etc.), the current availability of resources at different layers (sensor, edge, cloud), and the amount of processing power each task requires. The second one makes optimal decisions about when to offload tasks to higher layers depending on several uncertainties in the system and environment, such as network congestion, fluctuating workloads, and the battery life of devices. The last one itself follows two main strategies: full offloading, where the entire task is sent to external resources (edge or cloud), and partial offloading, where the task is divided, with some parts processed locally and others sent for offloading. By carefully considering these three aspects, the scheduler can make strategic decisions about computation offloading, achieving a balance between performance, efficiency, and optimal utilization of resources.

This chapter presents a dynamic approach to computation offloading, examining computation scale, data size, and communication latency in various scenarios, including two resource allocation methods (resource placement and resource scheduling) for two vital resources (response time and computation power). The proposed solution consists of formulating system behavior in various dataflow configurations, including comprehensive analyses from multiple perspectives. It also includes a dynamic offloading solution that compares these with static strategies to highlight their benefits in dynamic IoT environments.

7.3 Computation Offloading

The computation offloading model represents the computing devices in a three-layer IoT system using the notations S, E, and C. Here, S denotes the sensor layer, which comprises n sensor devices; E represents the edge device at the edge layer; and C signifies a cloud device. Each device runs an application over a specified period. These applications are characterized by a tuple $A_i = \{D_{in}, D_{out}\}$, where D_{in} is the amount of input data required for each application, and D_{out} is the output data generated by each application.

The model also defines the location where the application should be offloaded. The offload decision for the system is represented by a tuple $\alpha = \{\alpha^S, \alpha^E, \alpha^C\}$ where α^j represents the offload decision at layer j where$j \in \{S, E, C\}$. If the sensor layer executes the applications at layer j, then $\alpha^j = 1$; otherwise, $\alpha^j = 0$.

The goal is to achieve the lowest possible response time by selecting the optimal computation scheme based on the specific system conditions. This offloading decision tuple, which dictates the processing scheme, can be determined at design time or dynamically during the runtime to minimize response time.

7.3.1 Design Space

A systematic approach during the initial design phase is crucial for complex IoT systems to function optimally. This involves exploring all the key factors that can influence system behavior. The proposed model examines the impact of the following parameters on response time:

Communication Cost

Offloading computations to higher layers necessitates data transmission between layers. Therefore, communication plays a significant role in total response time. Here, the network packet loss ratio (β) is considered an affecting parameter to study the communication costs between devices in various scenarios.

Dataflow Configuration

The location of end-users can significantly impact communication costs. Any change in the data flow, from where data is collected, processed, and delivered, can directly affect system behavior. Two dataflows are studied with respect to the end-user location where the actuation response happens.

Dataflow 1: In this scenario, the entity that receives the result of the processing as a notification or actuation is located at the same layer as the sensors, and the sensor's processing unit can directly send instructions to the actuators at the sensor layer. This dataflow is labeled as *notification-via-wearable* in Figure 31. Data analysis can be performed on the sensor node itself, the gateway device, or even the cloud. The response time depends on the chosen processing layer:

- Local processing (sensor node): The response time is simply the execution time for analyzing the raw data at the sensor:

$$T^S_{res} = T^S_{exe} \tag{5}$$

  where T^S_{exe} is the execution time of analyzing raw data at the sensor layer. Labeled as A in Figure 31.

- Edge processing: Offloading analysis to the edge device adds transmission times for sending data from the sensor to the edge (T^{SE}_{trn}) and for sending the response back (T^{ES}_{trn}). The total response time includes these transmission times and the execution time on the gateway (T^E_{exe}).

$$T^E_{res} = T^{SE}_{trn} + T^E_{exe} + T^{ES}_{trn} \tag{6}$$

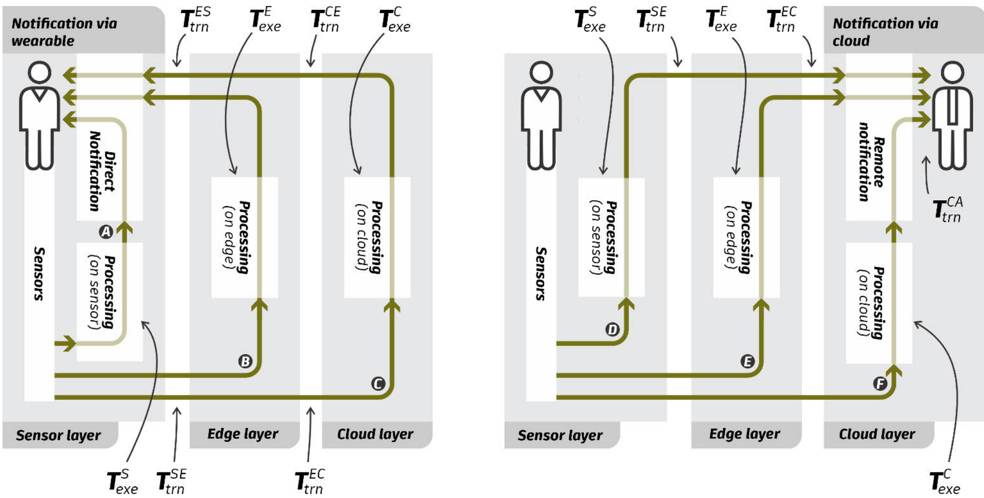

Figure 31. The IoT architecture illustrating the system components, two dataflow types, and the times consumed within each component.

It is labeled as B in Figure 31.

- Cloud processing: For tasks requiring even more processing power, the data is sent to the cloud. This adds significant round-trip transmission time between the sensor and the cloud ($T^{SE}_{trn} + T^{EC}_{trn} + T^{CE}_{trn} + T^{ES}_{trn}$) on top of the cloud's execution time (T^{C}_{e}).

$$T^{C}_{res} = T^{SE}_{trn} + T^{EC}_{trn} + T^{C}_{exe} + T^{CE}_{trn} + T^{ES}_{trn} \tag{7}$$

Shown as dataflow C in Figure 31.

Dataflow 2: This dataflow scenario applies to situations where the notification or actuation happens via a cloud service. Here, a network of sensors collects data, which is then analyzed across the layers and ultimately used to notify an end-user on the application layer. This is common practice in remote monitoring IoT systems. The end result (like a notification) is typically transmitted from the cloud layer to the end-user, assuming they are connected to the cloud. This dataflow is labeled as *notification-via-cloud* in Figure 31. The total response time depends on where the collected data is processed, as shown in the following equations:

- Local processing (sensor node):

$$T^{S}_{res} = T^{S}_{exe} + T^{SE}_{trn} + T^{EC}_{trn} + T^{CA}_{trn} \tag{8}$$

where T^{CA}_{trn} is the cloud-to-end user transmission time. This dataflow is labeled as D in Figure 31.

- Edge processing:

$$T^{E}_{res} = T^{SE}_{trn} + T^{E}_{exe} + T^{EC}_{trn} + T^{CA}_{trn} \tag{9}$$

  This dataflow is labeled as E in Figure 31.

- Cloud processing:

$$T^{C}_{res} = T^{SE}_{trn} + T^{EC}_{trn} + T^{C}_{exe} + T^{CA}_{trn} \tag{10}$$

  This dataflow is labeled as F in Figure 31.

We can represent the unified response time of both dataflows using a single equation:

$$T_{res} = \alpha^{S}.T^{S}_{res} + \alpha^{E}.T^{E}_{res} + \alpha^{C}.T^{C}_{res} \tag{11}$$

where $\alpha = \{\alpha^{S}, \alpha^{E}, \alpha^{C}\}$ is the offloading decision tuple. Here, only one α^{j} can be 1 while the others are 0. This tuple essentially determines which processing layer is chosen (sensor, edge, or cloud).

Application Complexity

Execution time can fluctuate depending on the workload arriving at a computing resource or the number of requested services. To ensure optimal design, the impact of application complexity is considered in response time calculations. Here, a new term is defined as an application characteristic to reflect how much data size increases due to computation. The Output-to-Input Data Generation (OIDG) ratio (γ) refers to the ratio of output data volume to input data volume generated in an application. To illustrate the impact of OIDG, four application categories are examined:

- Extremely Low OIDG ($\gamma << 1$): Machine learning classifiers process large input data into a few classes (e.g., image recognition).

- Low OIDG ($\gamma < 1$): Applications like compression or down-sampling reduce data size slightly.

- Medium OIDG ($\gamma \approx 1$): Noise filtering applications might not significantly change data size (samples per second remain similar).

- Extremely High OIDG ($\gamma > 1$): Applications like encryption or video decoding significantly increase data size due to processing.

By exploring these parameters, we aim to develop a comprehensive understanding of how to optimize response time through strategic computation offloading in IoT systems.

7.4 Model Exploration

Extensive experiments were conducted to examine how the mentioned parameters affected the system's response time. Various environmental conditions, application characteristics, dataflow configurations, and system complexity were explored during the system investigation.

- Applications: Four applications with varying OIDG ratios are chosen: i) an image object detector with γ = 0.001 ii) a video edge detector with γ = 0.043 iii) a video denoising with γ = 1 iv) a video decoder for object detection with γ = 95
- System Complexity: The number of nodes in the network is varied from 1 to 10.
- Dataflows: Two dataflows are considered: *notification-via-wearable* and *notification-via-cloud*.
- Communication: Packet loss ratio over the wireless network is varied from 0% to 14%.
- Network Connectivity: Communication between the edge layer and the cloud layer can utilize 3G (download 2Mbps, upload 1.1Mbps), 4G (download 13.8Mbps, upload 5.9Mbps), or Wi-Fi (download 55Mbps, upload 18.9Mbps) connectivity.

Figure 32 presents the results of the design space exploration. Each graph explores a specific combination of application type and dataflow configuration. Furthermore, each colored surface within a graph represents the response time under a particular computation offloading strategy. For example, the violet surfaces depict the response time when sensors execute the application locally, while the blue surfaces represent cloud processing with a 3G connection to the edge layer. Within each graph, the X-axis represents the packet loss ratio in the wireless network, the Y-axis represents the number of connected sensor nodes, and the Z-axis represents the response time. This visualization enables the analysis the effect of different factors (packet loss, number of sensors) on response time for various application types, dataflows, and offloading strategies.

As Figure 32 (f) explains, the overall response time is greatly impacted by the transmission time across various layers. It is observable that a system running a low OIDG application on a *notification-via-cloud* dataflow is notably influenced by changes in packet loss ratio. When the packet loss ratio is low, edge computing emerges as the most effective solution among other options, as indicated by the green plane being positioned lower than the others. However, in the case of a high packet loss ratio, sensor layer computing becomes the optimal solution. Here, an increase

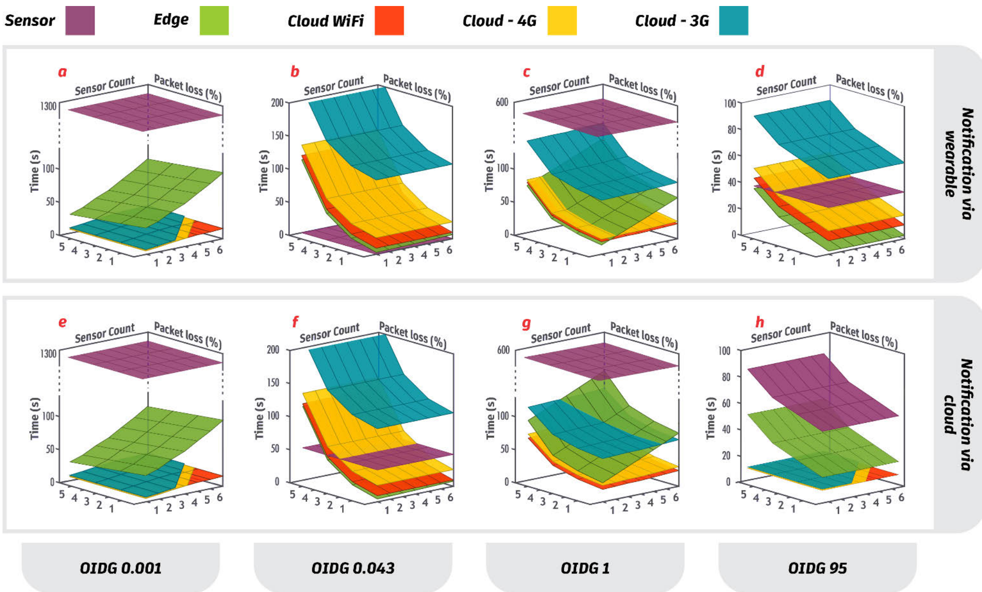

Figure 32. The computation offloading exploration for different environmental parameters and system complexity for chosen applications in two different dataflows.

in packet loss ratio results in a substantial rise in response time, highlighting the advantages of sensor layer computing under specific conditions.

Conversely, the packet loss ratio has no impact on the optimal solution in a system running an extremely low OIDG application with both dataflow configurations (refer to Figure 32 (a) and (e)).

The experiments also highlight how a growing number of connected sensors can significantly impact response time in complex systems. This is because multiple requests arriving simultaneously at a processing unit can overload it and slow down response times. Figure 32 (c) exemplifies this effect. For the scenario with a medium OIDG application using the *notification-via-wearable* dataflow, the optimal offloading strategy changes as the number of sensors increases. With a single sensor, edge computing is the best option. However, as the number of sensors grows, cloud computing over WiFi becomes more efficient. This is because the edge layer, located closer to the sensors, becomes more susceptible to congestion from simultaneous requests compared to the cloud layer. Therefore, in complex systems with many sensors, the optimal offloading strategy might need to dynamically adapt to changing conditions.

The plots are also showing that the end-user's location, where they receive notifications, affects response time. Considering an application with a high OIDG ratio (significant data size increase after processing), Figure 32 (d) shows that cloud computing is the worst option for *notification-via-wearable* dataflow (likely due to the additional communication hop to the wearable). However, Figure 32 (h)

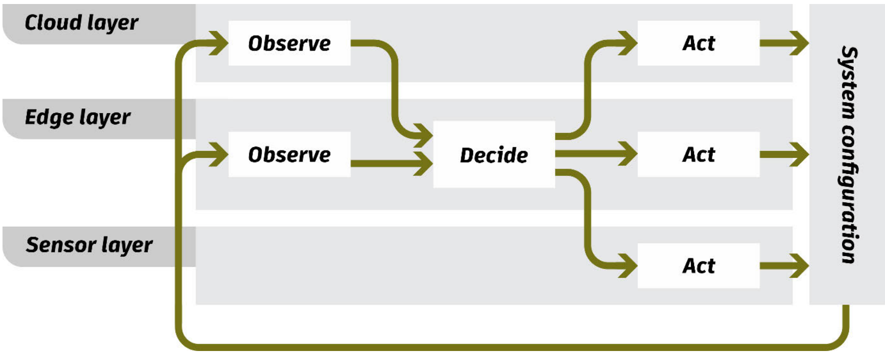

Figure 33. The positioning of the ODA model components within IoT System Architecture.

demonstrates that cloud computing can be optimal for *notification-via-cloud* dataflow (where the user is already connected to the cloud). This emphasizes that even with the same system complexity and environmental factors, the optimal dataflow can significantly impact the best offloading strategy.

Furthermore, Figure 32 (b) showcases another scenario. A system running a low OIDG application with *notification-via-wearable* performs optimally with local sensor processing. However, this might not always be the case for *notification-via-cloud*, where additional factors like network congestion between the sensor and cloud might come into play.

The OIDG ratio also significantly impacts system behavior. Applications with a higher OIDG ratio incur greater communication costs when delivering results to the user. Figure 32 (b) shows that for a low OIDG application with *notification-via-wearable*, processing data locally at the sensor layer is the most efficient approach. However, Figure 32 (d) illustrates that for a high OIDG application with *notification-via-wearable*, offloading processing to higher layers (potentially the cloud) leads to faster response times. This is because the additional data size after processing becomes a significant factor, and offloading reduces the amount of data that needs to be transmitted to the wearable device.

Furthermore, the study highlights that systems with high OIDG are more sensitive to packet loss. This means that data transmission errors can have a more significant impact on response time when dealing with applications that generate a much larger output size compared to the raw data.

7.5 Dynamic Computation Offloading System

The investigation of influencing parameters has guided the proposed resource management solution towards a dynamic offloading algorithm. This dynamic offloading approach used the insight obtained from the exploration phase for real-time decision-making.

This algorithm extends over the IoT architecture layers to perform the ODA

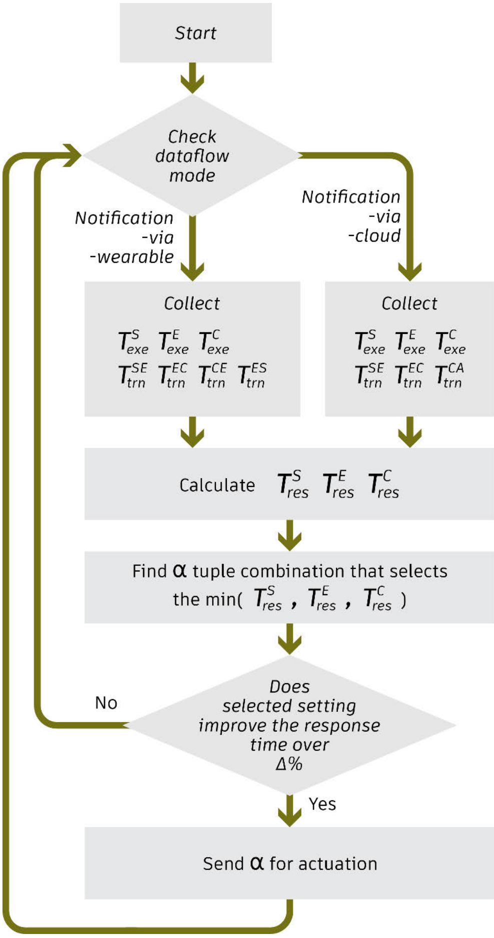

Figure 34. The dynamic computation offloading decision-making flowchart.

(*Observe*, *Decide*, *Act*) loop once again. As shown in Figure 33 the *Observe* stage spreads across the edge and cloud layers, gathering information about the system's current state, allowing it to be aware of its own performance regarding the application OIGD (self-awareness) and surrounding environment regarding the number of sensors, network speed, and packet loss (context-awareness). Within the *Decide* stage, situated entirely at the edge layer, the system analyzes the data collected in the *Observe* stage and determines the best course of action. Locating on the edge allows local decision-making, which can often be faster and more efficient than relying on the cloud. Once the *Decide* component determines the optimal processing location, the *Act* component in that layer takes the necessary steps to execute the computation. The *Act* component is divided across all three layers (sensor network, edge, cloud server) because computations can be migrated to any of these locations.

Figure 34 illustrates the proposed dynamic computation offloading algorithm in the form of a flowchart. When the system is initiated, the algorithm first examines the user-selected dataflow mode, which could be *notification-via-wearable* or *notification-via-cloud*. Each dataflow mode has distinct response time characteristics. Depending on the dataflow mode, the algorithm retrieves the execution time of the specific application on each layer, the required communication times between them, and the response time of each targeted layer for offloading. Subsequently, the algorithm identifies the layer with the minimum response time, which then becomes the new processing location. The α vector is updated to reflect this decision, with potential values being $\{1, 0, 0\}$ for the sensor, $\{0, 1, 0\}$ for the edge, and $\{0, 0, 1\}$ for the cloud layer. To prevent the system from constantly switching between layers with very similar response times, a "soft margin" (Δ) is introduced as a small percentage of the current response time. The α vector is only modified if the response time in the layer with computation minus the soft margin (Δ) is still higher than the response times of other layers. This ensures that the system only switches layers when there is a clear benefit in terms of response time.

7.6 System in Practice

A 24-hour extensive simulation is performed to evaluate the performance of the proposed model and the dynamic offloading solution using the insights obtained during the model exploration phase. The computation in the dynamic system is distributed across layers based on the conditions. Response time is assessed using static and dynamic methods. Initially, the dynamic solution conducts computations in the cloud layer. However, when packet loss and the number of connected sensors change, the dynamic system redistributes the computation to lower layers. In contrast, static approaches do not consider condition variations, leading to inefficient operation of the IoT system. Figure 35 describes the results showing that the average response time of the applications at the sensor, edge, and cloud layers is improved by 91%, 19.8%, and 7.8%, respectively, through dynamic solutions. This demonstrates that better performance can be achieved through dynamic solutions. Paper *V* provides the details of this simulation and more evaluation details of the proposed solution.

7.7 Summary

This chapter presented a resource management approach for two closely interrelated resources: computational power and response time. The proposed solution first formulates the behavior of a complex multi-sensor IoT system, exploring several affecting parameters, including communication cost, dataflow configuration, application type, system complexity, and network type. Then, it suggests a

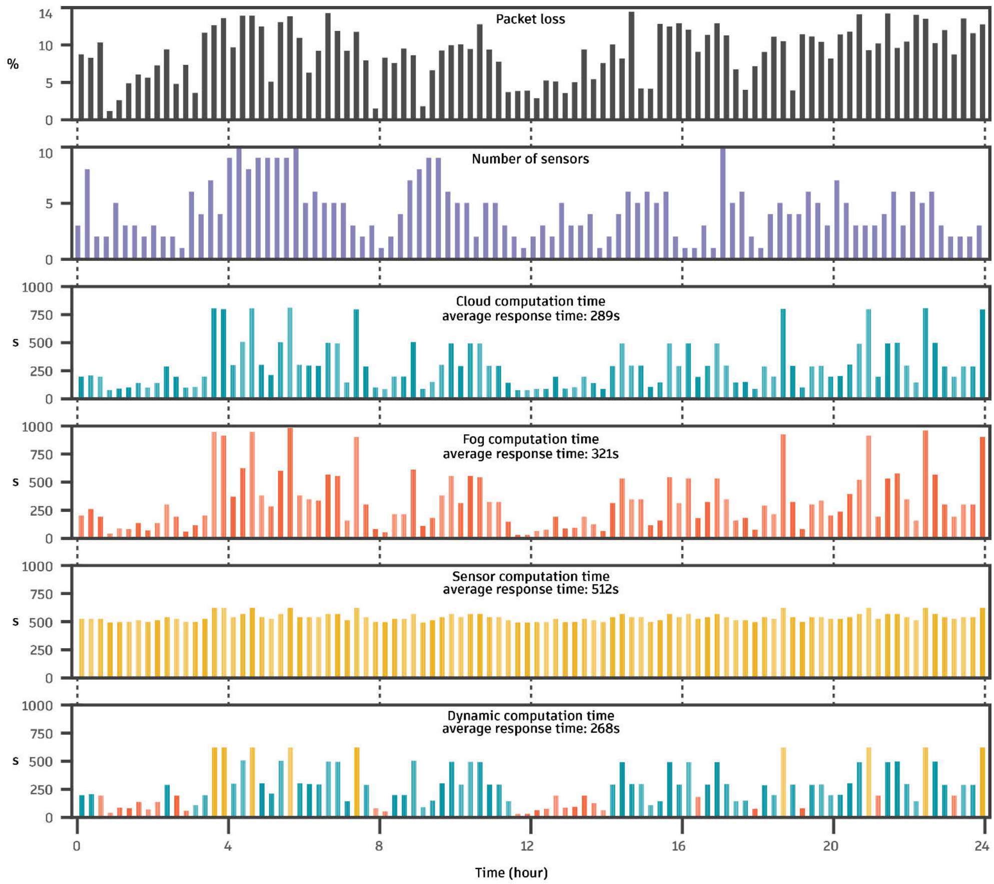

Figure 35. The overview of the dynamic offloading solution performance in practice.

dynamic computation offloading algorithm for transferring computational tasks from resource-constrained devices, such as IoT sensors or mobile devices, to more powerful external computing resources like edge devices or cloud servers. The model exploration phase revealed valuable insights about the response time within large-scale IoT systems, and the proposed dynamic offloading solution proved to increase the performance of the application execution within such systems.

8 Discussion

While this thesis was being completed, other researchers, scientists, and companies have advanced various aspects of wearable and IoT-based health monitoring systems. In recent years, the market for IoT-based remote health technology has seen a significant influx of wearable products. Companies have introduced a wide range of smart health monitoring devices, including smartwatches [83], smart rings [84; 85], chest straps [86; 87], arm and headbands [88], earplugs, and headphones capable of tracking heart rate [89; 90]. Additionally, connected devices such as scales [91], blood pressure cuffs for both arms [92] and wrists [93], bed sensors [94; 95], and Holter monitors [96] have become available. Beyond these, innovations include non-invasive blood glucose monitoring [97], smart clothing and fabrics [98], and mobile phone-based health monitors [99].

Recent advancements in sensor technologies include state-of-the-art photonic systems [100], flexible circuitry [101], and ultra-low-power components lead to more efficient and adaptable sensor designs, which improve accuracy, lower energy usage, and enhance portability. Moreover, progress in nanotechnology [102], microelectromechanical systems (MEMS) [103], and graphene-based sensors [104] has expanded the potential of IoT and wearable devices, facilitating the incorporation of intricate sensing features into compact, wearable formats.

Recent innovations in photoplethysmography (PPG) sensor design include flexible sensors [105], in-ear sensors [106], and multi-wavelength PPG technologies [107]. These developments improve the accuracy of PPG measurements, facilitating broader applications in wearable devices. Additionally, various studies have aimed to enhance signal quality by identifying and addressing low-quality data [108; 109] while extracting more reliable results from noisy information. This effort encompasses the use of sophisticated signal processing algorithms and machine learning techniques to boost data robustness and reliability [110].

When evaluating the current state-of-the-art regarding the implementation of Early Warning Systems (EWS) in IoT-based health monitoring systems, particularly in terms of efficient resource management and incorporating awareness features into system decision-making, it becomes clear that the substantial and innovative contributions in this research area are presented within the papers included in this thesis or authored by the author of this thesis. To the best of the author's knowledge, and aside from several review articles summarizing existing approaches, no other significant novel contributions addressing these specific aspects have been identified in the current literature.

Several studies have been published on resource management, including the location of computation in the network [111], load balancing [112], resource optimization [113], resource allocation [114; 115; 116], and resource scheduling [117]. In the area of self-awareness, several self-aware solutions are proposed for energy management and quality enhancement [118; 119].

Ultimately, with the recent advancements in AI, several areas remain open for the continuation of this research topic. AI-driven models can enable an IoT system to better manage resources and become more self-aware of its context and the subjects being monitored. By utilizing AI, the ODA loop can employ a pre-trained model as its decision component, responding to input that is, in fact, its observation. Furthermore, predictive analytics can forecast resource needs based on historical data and real-time monitoring, ensuring the efficient allocation of resources such as energy sources, bandwidth, and computational power. Through reinforcement learning, a system can discover its optimal settings through trial and error over time. Another enhancement for future work involves utilizing digital twins, which are integrated, data-driven virtual representations of real-world entities or processes. In this context, they represent subject and contextual behavior, allowing the system to be fine-tuned in the lab before real-world application. In the pursuit of sustainability, resource management can be improved by offsetting consumed energy through harvesting from the environment, thereby reducing the need for battery replacements and minimizing electronic waste.

These methods promise to unlock the full potential of IoT health monitoring systems, which relies on addressing key resource management challenges.

9 Conclusion

This research has addressed longstanding barriers to equitable healthcare access through advancements in IoT-enabled remote health monitoring systems. For decades, quality healthcare has remained inaccessible to many due to geographic isolation, resource limitations, and prohibitive costs. The emergence of miniaturized IoT wearables has begun transforming this landscape by enhancing real-time biomedical data collection and transmission in home environments. These systems provide continuous health assessments and facilitate early medical interventions—critical factors for managing chronic conditions and reducing hospitalizations. By condensing hospital monitoring capabilities into wearable devices, IoT-based health technologies effectively distribute healthcare resources, enable patients through self-management, and reduce strain on healthcare infrastructure. This transformation is particularly vital for aging populations and rural communities where traditional healthcare delivery models often prove inadequate.

The full potential of IoT health monitoring systems, however, cannot be realized without addressing fundamental resource management challenges. Such systems are naturally resource-constrained, and their continuous operation makes them highly resource-consuming. Without effective resource management strategies, such systems cannot be considered viable solutions. This study was motivated by the promising opportunities that IoT provides for remote patient monitoring and its potent architecture for hosting resource management strategies, which were not possible earlier with offline monitoring systems. The thesis approached the resource management challenges by dividing them into two interconnected stages: resource management during design time and runtime. These stages are not independent but rather require concurrent optimization for optimal results. Static resource management—such as selecting energy-efficient hardware during design—and dynamic resource management—which ensures real-time adaptability during operation—both play essential roles in optimizing system performance. This means that the system must be initially designed with reconfigurability in mind, along with other factors such as response times, signal accuracy, and power consumption, for the dynamic solution to be applicable to the system.

Therefore, in response to the challenge of managing resources in IoT-based health monitoring systems, this thesis studied four dynamic resource management approaches, each integrated with at least one static yet remotely reconfigurable system. These approaches were chosen because their features correspond to real patient monitoring situations. From a distinct perspective, a remote patient monitoring manager can be divided into four essential components: the system itself, the subject, the decision regarding the system and subject, and the deciding component. Thus, besides the rationale outlined in earlier sections of this thesis, the work can be summarized from this new perspective as well.

Concerning the first component, the system itself, self-aware resource management was explored, acknowledging that self-awareness is essential for a resource-constrained system to be aware of its own resources and have enough autonomy to act when not connected to the network. Regarding the second component, the subject and its surrounding context, context awareness was explored, acknowledging that environmental and behavioral factors significantly influence vital signs in remote monitoring scenarios. Referring to all actionable but conflicting decisions, goal management was studied to address the challenge of resource allocation according to situational priorities. Finally, to determine the system layer that hosts the processing part, computation offloading was investigated to evaluate how system components collectively contribute to desired outcomes.

When summarizing these approaches, it is evident that all of them adhere to a unified solution structured around the *Observe-Decide-Act* (ODA) awareness model, and each approach was designed to conform to this model. The self-awareness approach utilized the *Observe* component to monitor internal status, the *Decide* component to evaluate situations, and the *Act* component to implement optimized settings. Similarly, the context awareness approach employed this model to decide and act accordingly when observing the subject's environment, behavior, and health status. The goal management solution leveraged ODA to identify and implement optimal system policies aimed at minimizing data gaps between recharging opportunities. In computation offloading, this decision-making model made appropriate actions possible based on network quality and application complexity.

The Medical Early Warning Score model was another common approach presented in this thesis. The first three approaches incorporated EWS systems to evaluate subjects' health status—a standard tool for vital sign assessment. All signal processing efforts, quality improvements, and reliability enhancements contributed to these tools' ability to determine individuals' health status and generate appropriate notifications when abnormalities were detected.

The last common element in the EWS-enabled approaches for resource management was the use of the PPG signal as the source of most vital signs. We collected this signal using prebuilt sensing components but designed and built our own reconfigurable data collection systems within these resource management approaches. We calculated the heart rate, respiration rate, and blood oxygen saturation out of PPG signal. We demonstrated how the brightness of the sensor's light source or current consumption affects signal quality and also examined the impact of body movements on signal artifacts. We validated the results using other sources of the vital signs with higher standards, such as an ECG signal for heart rate validation, a nostril temperature-sensitive airflow sensor for respiration rate validation, and a medical-grade pulse oximeter to confirm SpO_2 calculations. The thesis demonstrated that with proper management of resources in a medical data collection system, the PPG—an active, high-power-consuming biomedical sensor—can be used reliably even in resource-constrained wearables. Motivated by the exciting possibilities IoT offers for remote patient monitoring, this thesis leveraged IoT-based solutions to implement resource management strategies, overcoming the limitations of traditional offline systems.

10 Publication Overview and Author's Contribution

10.1 Paper I - Edge-Assisted Control for Healthcare Internet-of-Things: A Case Study on PPG-based Early Warning Score

This paper presents an edge-assisted control system for healthcare Internet of Things (IoT) applications, focusing on optimizing resource allocation in remote health monitoring systems. The system utilizes a reconfigurable sensor node that can adjust its sensing fidelity and hibernation duration based on the patient's activity and health status. An edge-assisted controller is implemented to dynamically optimize the trade-off between energy efficiency and measurement accuracy. The system employs a modified Early Warning Score (EWS) method to assess patient health status, considering both vital signs and physical activity.

The proposed system includes a reconfigurable sensor node with adjustable sensing parameters, an edge layer for data processing and decision-making, and a cloud layer for long-term data storage and analysis. It uses a state machine approach to adjust sensing and hibernation durations based on patient state. A case study on PPG-based EWS monitoring is presented to demonstrate the system's effectiveness.

Experiments showed that the proposed system could significantly reduce power consumption while maintaining acceptable accuracy in vital sign measurements. The paper demonstrates how combining system-driven and data-driven optimization approaches can lead to more efficient healthcare IoT systems. Overall, this paper presents a novel approach to optimizing resource allocation in healthcare IoT systems by leveraging edge computing and context-aware sensing strategies.

Author's contribution: As the primary contributor and first author of this publication, the author played a central role in shaping the study. He took the lead in designing the research and developing the proposed system. He contributed to designing and implementing the reconfigurable sensing device and the reference signal data collection system. He was also involved in planning and carrying out the collection of both reference and test data, running the case study, and evaluating the proposed system's accuracy and performance.

10.2 Paper II - Energy-efficient and Reliable Wearable Internet-of-Things through Fog-Assisted Dynamic Goal Management

This paper presents a novel approach to energy-efficient and reliable wearable Internet-of-things (IoT) devices for remote patient monitoring through edge-assisted dynamic goal management. We propose a multi-goal, multi-policy system that prioritizes patient health status, monitoring continuity, and data accuracy while optimizing power consumption. The system uses a self-aware power manager that observes the patient's health status, activity level, and device battery status to dynamically select the most appropriate monitoring policy.

The proposed solution consists of four modules: observation, state detection, priority assessment, and policy enforcement. These modules are distributed across an IoT architecture's sensor, edge, and cloud layers. The sensing device periodically performs self-observation and sends data to the edge layer when significant changes are detected. The edge layer then assesses the patient's state and system status, determines priorities, and enforces an appropriate policy for the sensor node.

We developed a reconfigurable wireless sensor node to evaluate our approach and conducted experiments to find the most efficient settings. We generated 300 days of simulated activity patterns and tested various configurations. The results showed that the proposed system could reduce power consumption compared to a baseline system without goal management and prevent data loss due to battery shortage. The proposed approach can potentially enhance the effectiveness of monitoring chronic disease and early health deterioration detection.

Author's contribution: As the first author of this publication and the primary contributor and driving force behind the study, the author has contributed to the research and development of the proposed goal management solution, designed the modular model and configuration algorithms, and played a key role in developing the system hardware and required embedded software. Additionally, he has contributed to conducting simulation tests and evaluating the system's performance.

10.3 Paper III - Self-Awareness in Remote Health Monitoring Systems using Wearable Electronics

This paper presents a self-aware remote health monitoring system that enhances the traditional Early Warning Score (EWS) method for predicting patient deterioration. We propose integrating Internet of Things (IoT) technology with wearable sensors to enable continuous patient monitoring in and out of hospital settings. The system incorporates self-awareness principles to address challenges in personalization, situation dependency, and system constraints like energy efficiency.

The architecture comprises several key components: biosignal pre-processing, situation awareness, self-awareness core, attention management, and reconfiguration. The situation awareness module analyzes patient activity and environmental data to provide context. The self-awareness core adjusts the EWS calculation based on the patient's situation and assesses data confidence. The attention component adaptively tunes monitoring parameters to optimize system performance and data quality.

We demonstrate our system through experiments showing how it improves data reliability, adapts EWS calculations to patient context, and enhances energy efficiency. By validating input data and considering patient activity, the self-aware EWS avoids false alarms that occur with the conventional method. The system also dynamically adjusts sensor sampling and transmission rates based on the patient's state, reducing power consumption significantly compared to a non-adaptive baseline.

This self-aware approach enables more personalized and dependable health monitoring for out-of-hospital scenarios while improving system efficiency. Integrating contextual awareness and adaptive resource management allows the system to provide more meaningful health assessments and optimize its operation.

Author's contribution: The author is the first and main contributor of the study. He participated in the exploration of the self-awareness model and its potential for adapting Early Warning Score system for out-of-hospital cases. He designed and implemented the data collection system, proposed the reconfiguration solution, and developed the necessary dynamic edge services. Additionally, he collaborated in the final evaluation of the proposed system.

10.4 Paper IV - Hierarchical Dynamic Goal Management for IoT Systems

This paper discusses the need for hierarchical dynamic goal management in complex Internet of Things (IoT) systems. As IoT penetrates various application domains, systems are becoming more complex and versatile, often serving multiple applications with diverse and changing goals. These systems face challenges in managing goals due to limited shared resources and potentially conflicting objectives that may change dynamically.

Since traditional approaches addressing isolated goals are insufficient for this emerging class of IoT systems, we propose a hierarchical goal management approach to coordinate overlapping and conflicting goals while meeting desired Quality of Experience (QoE). This approach involves a predefined subset of goals and subgoals that can be dynamically modified, created, or removed; dynamic priorities for goals; periodic updates to fine-tune goal priorities; an inspection function to determine goal satisfaction; and a goal function for planning goals over time.

The paper presents case studies from two application domains: patient health monitoring and Cyber-Physical Production Systems (CPPSs). In the health monitoring example, we discuss conflicting goals at the sensor and edge layers, such as balancing accuracy and energy efficiency in data collection and transmission. For CPPSs, we explore challenges in resource allocation, anomaly mitigation, and self-configuration in distributed systems.

The paper emphasizes that hierarchical dynamic goal management can help resolve conflicts between local and global goals, improve system efficiency and robustness, and adapt to changing conditions. We suggest that this approach lays the foundation for future research in addressing the complex challenges of goal management in IoT systems.

The paper concludes by highlighting the need for new strategies, models, and algorithms to efficiently coordinate goals in IoT systems. We present our approach for hierarchical dynamic goal management as a step towards realizing more adaptive and efficient IoT systems across various application domains.

Author's contribution: As the second author of this publication, the researcher contributed to presenting goal management solutions in the healthcare domain, playing a key role in preparing the manuscript sections related to this aspect. The author presented and explored various healthcare domain case studies, providing valuable insights into the proposed system's practical applications. His studies in healthcare helped bridge the gap between theoretical concepts and real-world scenarios, enhancing the overall relevance and impact of the research.

10.5 Paper V - Exploring Computation Offloading in IoT Systems

This paper explores computation offloading in Internet of Things (IoT) systems with a three-layer architecture consisting of sensor, edge, and cloud layers. We investigate how various factors like dataflows, communication costs, system complexity, and application characteristics impact the response time in IoT systems. We highlight that previous studies often neglected important parameters like application output-to-input data generation (OIDG) ratios and dataflow configurations when determining optimal computation offloading strategies.

The paper presents a detailed analysis of response time models for two common dataflow configurations in IoT systems. Through experimental evaluations, we demonstrate that the optimal computation offloading solution can vary significantly based on network latency, dataflow configuration, application characteristics, and the number of connected sensors. We show that static offloading schemes are insufficient for dynamic IoT environments where conditions change frequently.

To address this, the paper proposes a proof-of-concept dynamic computation offloading technique using an *Observe-Decide-Act* (ODA) control loop. This approach continuously monitors system conditions, makes offloading decisions, and executes computations across the sensor, edge, or cloud layers to minimize response time. We evaluate our dynamic system over a 24-hour scenario with varying system complexity and packet loss ratios. Results show that the dynamic approach is capable of reducing average response time compared to static cloud, edge, and sensor computing schemes.

The paper concludes by highlighting the importance of considering a comprehensive set of parameters for effective computation offloading in IoT systems. It emphasizes the need for self-aware, dynamic optimization methods that can adapt to the unpredictable and changing conditions in IoT environments. Overall, our work contributes to a better understanding of the complex trade-offs involved in IoT computation offloading and proposes a promising direction for future adaptive offloading strategies.

Author's contribution: As the second author of this publication, the researcher collaborated on the initial formulation of the optimal location in the system architecture for performing computations, which formed the base of the presented dynamic approach for computation offloading. The author also contributed to the model exploration by analyzing, evaluating, and visualizing the system behavior. Additionally, he performed the execution of the dynamic computation offloading algorithm, providing insight for the final evaluation of the proposed solution.

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