Chapter

A Thermal and Energy Aware Framework with Physiological Safety Considerations for Internet of Things in Healthcare and Medical Applications

Amitabh Mishra

Abstract

Healthcare, lifestyle, and medical applications of Internet of Things (IoT) involve the use of wearable technology that employs sensors of various kinds to sense human physiological parameters such as steps walked, body temperature, blood pressure, heart rate and other cardiac parameters. Such sensors and associated actuators can be worn as gadgets, embedded in clothing, worn as patches in contact with the body and could even be implanted inside the body. These sensors are electronic, and any electronic activity during their sensing, processing and wireless transmission is associated with the generation of heat. This dissipated heat can cause discomfort to the subject and has the potential of damaging healthy living tissue and cells. In the proposed work, the author does a performance check on the intrinsic safety aspects of an IoT healthcare network with respect to the functioning of the wireless sensors involved and routing of sensor data samples. The author also suggests an optimized thermal and energy aware framework to address the issue of temperature rise due to processing and data transmission from sensors through signal processing approaches that help in reducing thermal hazards and simultaneously enhancing the network lifetime through energy conservation.

Keywords: Internet of Things, Internet of Things in healthcare, wireless sensors, safety considerations in IoT applications, power for wireless devices

1. Introduction

All living beings require healthcare and monitoring, and the requirement increases with age. According to the Department of Economic and Social Affairs of the United Nations Secretariat, the elderly population (persons of age 60 years and over) in the world in 2020 was 1049 million and is projected to be 1,198 million in 2025, or 15% of world population [1]. Healthcare is expensive and the treatment and its management require a lot of data collection. Occurrence of pandemics amplifies healthcare requirement for living beings of all ages, and more so for geriatric subjects, pressurizing the healthcare systems. Medical cost trends are increasing all over the world for multiple reasons and are expected to maintain an upward trend in the future, irrespective of the healthcare models used by the different countries in the world. According to a study by PricewaterhouseCoopers Health Research Institute, there will be a 7% medical cost trend in 2021, a percent above the trend in 2020 [2]. A study on healthcare spending by Peterson foundation reported that during 2019, the spending was close to $3.8 trillion, or $11,582 per person in the U.S. These costs are expected to climb to $6.2 trillion—roughly $18,000 per person by 2028 [3].

2. Requirement of a new system for ubiquitous health monitoring

In most healthcare systems, rocketing expenses, insufficient staffing, medical inaccuracies, and the incapability of the patient to get to a hospital in time are adding to the workload of the already overloaded existing healthcare provisions. Vital parameters for living subjects often require monitoring that needs appropriate sensors. Use of wires for sensor data transfer requires the patient to be either stationary or that sensors, electronics, wires, and human-machine interface (HMI) unit, all move with the subject. A wired monitoring system impacts the mobility of the subjects. It is also a major inconvenience to patients if they must visit hospitals every time for getting the readings of vital parameters taken. Such monitoring done only during hospital visits is not continuous, gives the healthcare professionals merely a snapshot of the patient's health parameters for a short time window, and is hence neither efficient nor perfectly reliable. Mobility of geriatric patients using such a wired system could be even more difficult. Quite a few times, the subject does not need to be confined to a bed and the health parameters still need to be monitored. The traditional healthcare monitoring sensor system designed using wired connections is cumbersome and impracticable for such applications.

There is a strong need for ubiquitous and pervasive monitoring of physiological, biochemical, and physical parameters in any environment without activity constraint and behavior alteration for managing patients with chronic ailments and geriatric care. Other important use cases could include general monitoring of well-being of any subject, performance evaluation of sportspersons and deployed soldiers and other applications involving travel and distant patients.

With recent advances in wireless technologies, it is possible to get rid of the wires and relay the data from the sensors to the HMI unit over wireless links, often via multiple hops across wireless transceivers built into the IoT sensors, thus creating an Internet of Things - Healthcare Sensor Network (IoT-HSN) that can exist in or around the subject's body.

To address the design requirements of an IoT-HSN, the technical issues that need to be focused on include the necessity for wearable or implantable devices with better sensor design, power source miniaturization with possible energy harvesting, biocompatibility, Micro Electro-mechanical Systems (MEMS) integration, low power wireless communication, secure data transmission and seamless incorporation with smart therapeutic schemes. The design would also benefit from redundancy and complementary sources of data to boost the information content and lessen systematic and random errors in sensor data. What is even more important is that such a system must do this inexpensively.

Non-intrusive, ambulatory, continuous, yet economical health monitoring systems using IoT-HSNs are now being developed to achieve a better and complete picture of health diagnosis and reduce the cost of healthcare. In this approach, multiple miniature, battery-powered, networked wireless sensor devices can be attached to or implanted inside the subject's body. These devices sense and collect data on subject's vital signs and transmit the data wirelessly to a central device implemented in a personal digital assistant (PDA) or a smartphone that collects and sends the data to a base station over an external network making them available to healthcare personnel for further assessment and analysis. The system obviates the need for wires that restrict the subject's movement and confine the subject, thus making ubiquitous but unobtrusive monitoring possible.

While IoT-HSNs are extremely useful and the need of the day, human tissue can be harmed by the heat produced by the electronic circuitry for the sensor node and antenna. This paper tries to address this issue related to IoT-HSNs in a novel way at the physical and data-link layer level.

3. Primary motivation for the development of IoT-HSNs

For prevention and complex intermediation, clinical practice relies heavily on early, truthful, and thorough diagnosis supported by tight scrutinizing of the results. To obtain qualitative and quantitative data for physiological parameters for living beings, a variety of sensors have traditionally been in use. These sensors need to convey their data to an HMI unit that can collect, analyze, and display the data in a variety of formats for use by healthcare personnel and store the data for future use. Traditionally, such data is relayed over wires to the HMI unit. The complexity of such a system increases with the number of physiological parameters being monitored. However, for the most part, this practice depends on a sequence of snapshots of physiological, bio-mechanical, and biochemical data which might not capture transient abnormalities reliably. An objective determination of a patient's recovery after diagnosis can be tricky due to the episodic and subjective nature of outpatient clinic assessment.

Vital signs monitoring systems for hospital ward-based patients have a propensity to be intensive on labor as they involve manual measurement and documentation, which also makes them prone to human error. Such systems restrict patient movement which might be redundant in several cases and can be benefited immensely by using wireless sensors. Automation of this process using wireless sensors with the capacity to pervasively observe patients wherever they are, not just on a hospital bed, is suitable to the patient as well as the healthcare provider.

Acute as well as chronic disease management through clinical medicine, health monitoring and healthcare delivery need to involve home and community settings and require radical changes in system design. Close monitoring of some patients needs to be made possible with safe early discharge without hospitalization being necessary, also reducing the cost for the patient and improving hospital bed availability. The pandemic has already proved that availability of hospital beds and their management can be extraordinarily challenging and critical at times.

3.1 A special case: Elderly patients

There are rapid changes happening in the social and economic structure of our society connected to demographic variations associated with increase in vulnerable aging population living alone, a sizable part of which constitutes the high-risk group that would benefit immensely by regular and non-intrusive healthcare monitoring. The volume of this group is set to expand, along with its prospective need upon healthcare resources because people in industrialized countries are living longer than ever before and average life expectancy has improved to more than 65 years [4].

The incapacity of the elderly residents to get medical assistance early enough for simple and treatable conditions may lead to substantial morbidity. Inclement and extreme weather conditions and the fact that they live alone could be two major factors responsible for delayed medical intervention that could make things worse.

It is an additional consideration if they live in rural areas. There is an acute need for unobtrusive monitoring of such patients in their home environment in any weather for earlier detection of any worsening in their condition, so that they can be promptly treated, thus reducing the necessity for hospital admission, related morbidity and even chances of mortality.

3.2 Novel trends involving lifestyle modifications

In recent times, the focus of healthcare also altered towards the general health and wellbeing of the populace rather than just the supervision of disease advancement or the effectiveness of therapeutic processes. Several healthy people actively monitor their health parameters because of increasing awareness towards healthy living these days. This is required for patients as well. Certain critical health-related events might not occur in the time window when the patient is in front of healthcare professionals. Such events could be missed, make a difference to the diagnosis and treatment, and thus create room for error. Therefore, several patients require health monitoring although they do not have to live in a hospital for this purpose.

Health is defined as "a state of comprehensive physical, mental and social well-being and not simply the non-existence of illness of infirmity" by the World Health Organization (WHO) [5]. Blocking disease through campaign of healthy lifestyle choice is a prospective cost-effective methodology to address contemporary healthcare risks [6]. The healthcare approach is shifting towards watching lifestyle behaviors and intervening when essential.

Selections such as smoking and alcohol, diet, sleep, physical activity, have all been linked with numerous medical conditions. The cardiovascular disease is one of the most documented illnesses related to lifestyle choices today [7]. Undesirable lifestyles that lead to chronic conditions need to be advocated against, in favor of promotion of healthy living with prevention and early intervention of ailments. There is plenty of evidence to link inactivity with poor physical condition which is why physical activity monitors are commonly available today and are still evolving for better efficiency [8].

The user-friendly software that comes with these activity monitor sensors is true value addition because it permits customized activity targets to be established, and progress towards those targets to be presented at any time or archived and examined later. The software can help with weight monitoring and management as well as diet tracking. Such monitors have demonstrated that they enhance quality of life as much as expensive, overseen workout programs [9].

3.3 Some prominent challenges for IoT-HSN applications

Anomalies of heart rhythm (arrhythmias) are frequently confronted in clinical practice, affecting almost 4% of the populace beyond the age of 60, rising with age to roughly 9% in people above 80 [10]. Heart failure affects up to 10% of patients who have attained an age of 65 years [11]. Early symptoms of atrial fibrillation arrhythmias include fatigue and palpitations, and often lead to the patient seeking medical advice. Averting the longer-term issues of tachycardia (rapid heart rate induced) involving cardiomyopathy (expansion of the heart causing pump failure) and stroke in such patients becomes crucial. Prospective bleeding problems caused by anticoagulant medication affect an escalation in mortality in this geriatric patient cluster, in addition to other risk factors [12]. Continuous and pervasive monitoring of heart rate is desirable for several patients and the elderly.

One of the principal vital signs, the systemic arterial pressure (ART) outcomes from the pressure exerted by the circulating blood in the large arteries and is then measured within large arteries in the systemic circulation in mmHg units. The parameter is dependent upon cardiac output and total peripheral resistance and its value varies with each heartbeat in accordance with the pumping action of the heart. All levels of ART exert some systematic stress on the arterial walls. Arterial pressure directly relates to cardiac output, arterial elasticity, and peripheral vascular resistance [13]. It is vital for the subject's body to be capable of adjusting to acute changes in arterial pressure and for the subject to obtain medical therapy or lifestyle modifications for chronic variations. Arterial pressure regulation is required to sustain a sufficiently high pressure that permits appropriate perfusion of body organs and tissue; but not high enough to cause harm. The connected medical condition is known as essential hypertension and is seen in roughly 95% of patients with hypertension [14, 15]. Treating hypertension is crucial because it can cause cerebral, cardiac, and renal problems. As it is a key parameter connected to the cardiac condition of the subject, the author decided to choose the analysis of this parameter as a representative of vital signs for the present work while the author dealt with data for several other equally important parameters.

Atrial fibrillation is known to have several associated complications such as hypertension or high blood pressure. High blood pressure is known to affect nearly one billion persons globally [16] and can relate to cardiac problems. Early identification of hypertension is vital, but its monitoring can be labor-intensive and might involve several clinic visits.

4. Technological advancements in favor of wireless health monitoring

The technology for new biological sensing modalities has started emerging and it aims at basically transforming the way we utilize bio-measurements in a truly customized monitoring platform that is smart and context-aware, yet imperceptible. An IoT healthcare sensor network (IoT-HSN) consists of one or more wireless sensor devices positioned on, in, or around the human body. The sensor devices sense and collect data from the human body and then transmit the data to a central device, called a Coordinating Sink Station (CSS) or simply sink, that can be implemented as an application in a smartphone or PDA. After collecting all information, this sink then forwards the data to the medical workers through external networks.

Thus, the idea behind an IoT-HSN is to perform the monitoring of human well-being in a "ubiquitous" and "pervasive" way keeping an eye on physiological, biochemical, and physical parameters in any environment – home or hospital, without constraint of activity [17, 18]. This idea is rapidly converting to reality with the key innovations in sensors, processor miniaturization, and wireless technologies for transmission of sensor data [19, 20].

Telestethoscopy is one such application in which electronic stethoscopes created by adding a capacitive diaphragm sensor with microphones and piezoelectric crystals [21] are making remote cardiopulmonary examination of patients in their home environments possible [22].

Innovations in crucial areas such as miniaturization of power supply, enhanced battery time, lowered energy intake, and power scavenging are vital to the design of such systems and are fast becoming a reality [23]. Use of customized wireless sensor network (WSN) technology for creating pervasive healthcare systems will permit access to truthful medical information irrespective of place and time and will go a long way in improving the quality of healthcare services.

Due to the restricted bandwidth and power constraints in an IoT-HSN, the optimality of conventional method of data acquisition followed by post transmission digital conversion and signal processing is questionable. While it requires resources, bio-inspired local processing at the sensor front-end prior to transmission, combined with behavior profiling, pattern recognition, and machine learning can yield highly optimized bio-monitoring systems.

5. Why IoT-HSNs are different

An IoT-HSN has more challenges than other wireless sensor networks because of several reasons, the most important of them all being the involvement of living subjects. The various design considerations for IoT-HSNs involve size, cost, reliability, data privacy, security, and intrinsic safety of the subject. This paper tries to address some of these issues concerning the intrinsic safety aspect of IoT-HSN design and the energy efficiency of an IoT-HSN.

WSN technology has benefited by miniaturization and cost reduction in creating sensors with computers and wireless transmission capability that are smaller than the size of the pin head [24–27]. Sensors that can be combined, run on low power, communicate over wireless links, and self-organize into a network have been used in oil and petroleum exploration and industry [25, 28, 29], structural monitoring [29], habitat monitoring [30] and smart homes [31, 32]. Security and scalability of IoT applications and services could also be an issue as addressed in this project aimed at building a Smart Independent Living for Elders (SMILE) home [33, 34] that the author is a part of.

However, the equipment used for these applications cannot address the specific challenges related to human body monitoring. The human body comprises of a complex internal ecosystem that reacts to and interacts with its external environment while staying distinct and self-contained. Hence, although an IoT-HSN is similar in operation to a regular WSN, it comes with an additional set of new challenges. It involves a smaller scale network (made up of miniature sensor nodes each having a small processor, wireless transceiver, and power) that requires a different type and frequency of monitoring and is capable of seamlessly integrating with home, office, and hospital environments.

The IoT-HSN sensor node guarantees the perfect gathering of data from the transducer element used, performs low level local processing of transducer data, and then transmits this data to a Local Processing and Coordinating Sink Station Unit (CSS). The data from all the sensors is collected by the CSS by this method, processed further, fused, and transmitted wirelessly to a central monitoring server [35].

As pointed out earlier, while some of the challenges faced are common to IoT-HSNs and WSNs, there are intrinsic variations between the two, which require special consideration in case of IoT-HSNs. Some of these sensors need to be implanted inside living human tissue. The power source for IoT-HSNs, if exhaustible and hence with finite lifetime, could be inaccessible and difficult to replace in an implantable setting. Energy is more difficult to supply, hence lower the requirement (with options of energy scavenging), the better. Loss of data in an IoT-HSN can be intolerable and may necessitate extra actions to guarantee quality of service (QoS) and real-time data examination capabilities. Human body is capable of movement, so an IoT-HSN is a mobile and dynamically changing network. Motion artifact is a major challenge in IoT-HSNs. Early detection of adverse events is vital in IoT-HSNs because failure of human tissue cannot be reversed. High level security for wireless data transfer is necessary to safeguard patient information and privacy. All these factors change the sensing modalities for IoT-HSN.

6. The temperature rise problem: prior work

IoT-HSN sensor nodes could be located on, around, or inside the human body, with each dissipating some part of its energy consumed as heat and causing temperature increase in its locality. Signals carrying sensor data need to travel through tissue (bones, flesh, and fluids). The longer a node works and transmits/receives data, the more energy is dissipated and converted into heat. Nodes not transmitting or in sleep with low power might not produce significant heat. However, continuous node operation over a period generates heat that cannot be ignored. When implanted nodes are being considered, this generates even higher concern. To balance the heat, the human body has a thermoregulatory system. If the rate at which heat is generated is greater than the rate of working of the thermoregulatory mechanism, the temperature rise can harm the human tissue that absorbs the heat. The temperature rise directly influences human safety and health adversely, as explored in [36, 37].

Due to the lossy nature of the human body, the sensor data might hop through intermediate sensor nodes before reaching the sink node instead of being communicated in a single hop. Natarajan et al. [38] attempted to compare the trustworthiness of single-hop and multi-hop network topologies.

The operation of node circuitry and radiation due to transmission from the antenna produce and discharge heat to the node's surroundings, which can be injurious to the subject's body cells beyond a safety threshold. Specific absorption rate (SAR) is a standard quantity that shows the power dissipated per unit mass of tissue. It is a well-known parameter regarding the electromagnetic safety towards the human body and is defined as a measure of the rate at which energy is absorbed by the body when exposed to a radio frequency electromagnetic field, expressed in W/kg [39]. For near-field exposures the upper bound of SAR is 1.6 W/kg for some tissue averaged over a gram according to the Federal Communications Commission (FCC) standard in the United States and is 2.0 W/kg for 10 g of tissue according to the International Commission on Non-Ionizing Radiation Protection (ICNIRP). These SAR values can be translated into temperature rise [36], with the maximum permissible temperature rise in the human head and brain being 0.31°C and 0.13°C (FCC) and 0.60°C and 0.25°C (ICNIRP). The report in [37] also suggests that a temperature increase of 0.1°C is sufficient to cause intense thermoregulatory responses in the human body.

According to a survey on thermal effects of bioimplants by Lazzi [39], the electromagnetic fields induced in the human body and the power dissipated by the implanted sensor nodes are the two main sources of temperature rise. The power dissipation is from three sources: caused by the stimulating electrodes, the implanted telemetry coil, and the implanted microchip.

The in-vitro (implanted) sensor nodes can transmit and receive the data only through a wireless system. The SAR measures the rate of energy absorption by the body per mass of tissue upon exposure to a radio frequency electromagnetic field. It is a standard parameter connected to the electromagnetic safety regarding the human body, expressed in W/kg. According to IEEE standards the acceptable value of SAR is 1.6 W/kg averaged over a gram of tissue and is used for cellular phones by the FCC.

A better hardware design with node and antenna running on lower power can reduce the heating effects. Also, a well-designed network routing protocol could reduce the bioeffects. This work tries to reduce these heating effects even further by reducing the amount of transmission, while trying to preserve the integrity and accuracy of the data within low limits of error as a trade-off of the suggested framework.

6.1 Routing based approaches towards solving the temperature rise problem

As briefly touched upon in the previous section, one of the topmost concerns in the design of IoT-HSNs involve monitoring the heat generated because of operation of sensor network nodes. Electronic activity in the sensor circuitry and antenna radiation dissipates as heat. Power is dissipated by the implanted sensor node electrodes, microchips and the electromagnetic fields induced in the human body from telemetry coils as heat which can cause harm to healthy cells and tissue [40, 41]. For burst data operations that do not last long, such heat can be overlooked. However, when the node is operating continuously, transmitting, and receiving data over a considerable period, the heat generated by the node cannot be neglected. This concern becomes even bigger when dealing with in vivo sensor nodes (i.e., implanted inside the human body). The human body has a thermoregulatory mechanism to balance the heat around the body. However, when the heat received rate is larger than the thermoregulatory mechanism rate, the temperature will rise and, in turn, damage the human tissue.

Routing overheads have a potential to cause additional heat damage. Also, extra energy might be required to implement thermally aware routing algorithms. The challenge is complicated by the fact that the heat and energy consumption, both these factors need to be lowered, because the sensor nodes run on the limited power resource of batteries, while the network throughput needs to be maximized. A trade-off needs to be reached in the design to address these diverse requirements.

There are three types of routing used on IoT-HSN protocols. First, proactive routing where each node has information about the neighbor nodes. Second, reactive routing where the node explores the information about the neighbors when there is a packet to be sent. Third, a hybrid which combines the benefits of two methods (e.g., protocols that use proactive in setup phase and reactive in data transmission phase).

Some approaches to reduce the risks of this heat damage involve designing routing protocols for IoT-HSNs that include temperature into the routing metric to decrease the heat.

The challenges related to IoT-HSNs have been proposed to be addressed through numerous routing protocols. Some approaches have tried to tackle the issue of extreme and dynamic path loss observed in intra IoT-HSN communication caused by postural movement of the subject's body. The routing scheme by Quwaider and Biswas [42] proposes division of the sensor field combined with store and flood mechanism to route the sensor data towards CSS. Their work in [43] uses a store and forward approach for a delay tolerant intra IoT-HSN communication.

The proposal in [44] uses a field partitioning with store and forward like in [42] based on if or not the sensors have a clear line of sight for communication. The storage of packets in these works makes the routing non real time making the scheme impractical for vital medical applications. The proposals do not take the heterogeneous nature of IoT-HSN data and the thermal effects into account.

In [45] the routing protocol uses a Temperature Aware Routing Algorithm (TARA) to reduce the thermal effects IoT-HSN operation by estimating the temperature rise in neighboring nodes to avoid hotspot nodes. The trade-off involves a delay in routing sensor data packets and additional energy requirement. The Least Temperature Rise (LTR) algorithm [46] tries to address this limitation by associating a hop-count with each data packet and use it for deciding to discard the packet if the hop count reaches a limiting value. The trade-off in this case is poor packet delivery ratio. Adaptive Least Temperature Rise (ALTR) algorithm proposed in [47] is also a thermal aware scheme that uses shortest hops to route packets instead of dropping them. Least Total Route Temperature (LTRT) algorithm [48] observes the temperature across the entire route instead of individual nodes or hop-count for routing decisions. None of these schemes consider the dynamic intra network path loss or the QoS parameters of heterogeneous IoT-HSN data, making their utility questionable.

Djenouri and Balasingham [49] propose to divide the vital sign data into four categories based on data criticality, thus allowing for delay in some parameters and employ two sinks for all data. The latter feature increases network traffic. Razzaque et al. [50] tried to improvise on [49] by using multi-hop transmission to meet QoS requirements of data packets but their algorithm performs poorly on data packet delivery. QoS aware routing used in two proposals by Khan et al. [51, 52] involves classification approaches that are variants of [49]. None of the QoS-aware routing schemes take inter IoT-HSNs communication, path loss or temperature issues into account.

Monowar et al. [53] and Bangash et al. [54] claim to propose QoS as well as thermal aware routing schemes for intra IoT-HSNs. Both schemes classify the sensor data as in [49, 50]. Monowar et al. [53] propose to send multiple copies of data to counter delay issues. This generates redundant additional network traffic, causes congestion and packet drops despite higher energy requirements and rise in temperature while neglecting the dynamic path loss. The proposal by Bangash et al. [54] performs better on these factors but fails to address the issue of reliable, timely delivery of critical data.

Critical Data Routing (CDR) proposed in [55] classifies data into critical and noncritical categories while considering path loss, temperature rise and QoS with decent performance. However, the scheme could benefit by considering additional measures for conserving network energy, which it does not focus on.

The approach in [56] suggests a Media Access Control (MAC) protocol that resorts to shortest hop routing of sensor data packets based on hop counts using a duty cycle decided upon by using the current temperature rise. The duty cycle is calculated using four probability distribution functions- Poisson, Binomial, Log-normal and Laplace. This protocol was chosen by the author for the current article as no other protocol blends thermal awareness with efficient duty cycles. The work uses three models. Of these, the Sensor-Centric Monte-Carlo model (SCMC) involves random sampling from a given finite space [57] while acquiring any temperature rise right from the sensor and not from the surrounding tissues. In the Tissue-Based Fixed Coordinator (TBFC) model, a grid divided control volume of tissue space is considered, like [39, 45, 58] which assumes that the entire IoT-HSN or a major portion of it is within this tissue control volume. The results indicate least packet loss of 30% for Poisson distribution on the duty cycle with the trade off with 80% active nodes that need more energy for IoT-HSN operation. The packet loss was further reduced by enhancing the working of TBFC by adding 1-hop caching mechanism (TBFC-1HC) in which data packets are cached before the node goes to sleep state if the node has not reached its sampling state while the next hop node might be mere one hop from the CSS.

None of these approaches address the issue of improving upon network lifetime. As the approach in [56] provides for best possible compromise for intrinsically safe, thermal and energy aware IoT-HSN design, the author chose on using it for further optimization and improving upon the energy scenario and network operation lifetime.

7. Framework for a novel IoT-HSN with energy awareness enhancement on thermal routing model

The author proposes a model which not only addresses temperature rise but is also energy aware and helps in improving network lifetime. For this study, the author used the same IEEE 802.15.4 Wireless based IoT-HSN schematic modeled for [59] to run in the CSS. The 24 channels in the IoT-HSNs were used to mimic relaying of physiological parameters from the subject such as parietal and occipital electroencephalogram (EEG), electroculography, respiratory airflow, oxygen saturation %, heart rate, pacemaker diagnostics, electrocardiogram (ECG), arterial and central venous pressures, respiration rate, thoracic and abdominal resistance, blood pressure and temperature, blood sugar and insulin levels, urine creatinine, nerve conduction, musculature actuator and electromyography (EMG). The study did not involve any human subjects directly because the data utilized were obtained from Physionet [60], a public research database. Of the 24 channels, 3 were used for bioactuators and the remainder were utilized by sensors. **Figure 1** shows the biosensors and bioactuators using an adhoc link to communicate with the coordinating sink station which was connected over an adhoc link with the body area network (BAN) gateway which in turn links the biosensors to a IoT-HSN base station. To demonstrate the in-depth analysis and to evaluate the performance of the thermal and energy aware framework proposed in this article, the author has used the arterial pressure parameter from the 24-channel model in the following sections.

Figure 1 shows four different 24-channel IoT-HSNs P1 to P4 in the vicinity of each other trying to send data to the base station with their performance possibly affected by radio interference. The channels in the IoT-HSN have 802.15.4 adhoc links to the BAN gateway for data transmission. Subsequently, the data is sent through a router to the base station. IoT-HSN P2 transmits its data to a different wired base station that exists on the same subnet. IoT-HSN P3 attempts to send data to its base station which is in a different subnet and uses a second router for connections. The base station for IoT-HSN P4 is a wireless node linked to the wired network via an access point. As human subjects can have different sizes, the placement distance for biosensors varies in the four IoT-HSNs.

7.1 Performance check on intrinsically safe routing models

While assessing the accomplishment of an IoT-HSN, it becomes vital to evaluate the intrinsic safety aspect of the wireless system and the possible risks of damage to healthy human cells and tissues. As pointed out earlier, the heat generated because of dissipation of wireless energy can cause discomfort to the subject and has the capacity to damage healthy human cells and tissues if endured for long times. For instance, the incessant monitoring of peripheral capillary oxygen saturation (SPO2)

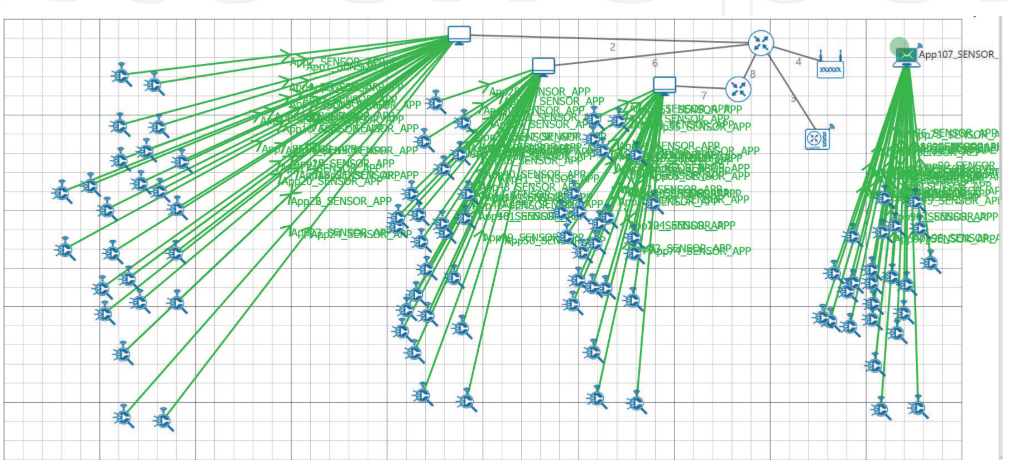

Figure 1.
Four 24-channel IoT-HSNs in action.

levels using a pulse oximeter for over 8 hours would cause a rise of temperature of 43 degrees Centigrade and is hence deemed risky as it could cause burns [61]. The detrimental effects of such sensor radiation caused heating can be evaluated by applying Penne's bio-heat Equation [62] that offers the heat transfer relationship between the temperature of blood vessels and the tissue surrounding the vessels. IoT-HSNs can follow temperature-aware routing algorithms [63–65] that consider parameters like antenna radiation and the ensuing power dissipation as temperature rise in the surrounding tissue and make routing decisions to minimize the generation of heat. Combined with an efficient MAC protocol, the thermal-aware routing algorithms can be used for generating transmission and sleep duty cycles that allow a reduced rise in temperature than individual schemes [56]. Although the outcomes in [56] are improved over the other attempts at temperature-aware routing, the approach does not take into consideration the base network energy requirement and additional energy consumption required for retransmissions of lost sensor data. The author attempted to estimate the implementation of the three models in [56] with regards to energy in a network involving actuator control applications with sensors for Internet of Things Healthcare Sensor Networks. The model in [56] uses up to 25 sensors in its IoT-HSN, which is very close to the author's model involving 24 sensors [59].

All the models considered in the present evaluation study the effect of four probability distributions for network parameters in addition to temperature rise, namely Poisson, Laplace, Binomial and LogNormal. Of the three, the SCMC model is a sensor-centric model that permits a random generation of packets based on a probability distribution while presuming fixed rise and fall in temperatures. A stable solver comprising of a fixed CSS is employed in the TBFC model for a stepped packet generation to offer improved heat performance than the SCMC. The trade-off for the TBFC model is a higher packet loss which is improved in the third model (TBFC-1HC). This modified TBFC model employs 'one-hop caching' in sensors to cache data packets for transmission delays up to their one hop neighbor that is nearest to the CSS. Data packets wait for a clear-to-send signal after which they are transmitted to the CSS.

7.2 Performance evaluation on traffic parameters of the model

The thermal aware routing algorithms for reducing the amount of heat generated have a trade-off in the form of loss of packets. The lost packets need to be retransmitted. The author tried to assess the data overhead due to retransmission resulting from packet loss for the four distributions across the three models. The results of the comparison can be seen in **Figure 2** below. It is evident from the results that of the three models, TBFC fared the worst on the retransmission of packets that were dropped, while SCMC was found to be the best. Comparing the retransmission overhead for the distributions, the Poisson distribution had the lowest values while Log-Normal had the highest retransmission overhead among the four distributions. The work has the potential to be extended by including other distributions involving a more realistic human model.

Even if lost transmissions cause additional data traffic due to retransmissions, a data transmission scheme that involves reducing the frequency on transmissions of the sensor data and sending alternate samples as suggested by the author in the next section would effectively cut down the heating effects in the same proportion. Merely skipping alternate samples would reduce the amount of heat generated to half, thereby allowing longer node operation. If the final recreation does not alter the doctor's initial diagnosis, the sample cut rate can be increased, thereby improving the heat performance to three or even four folds of the default.

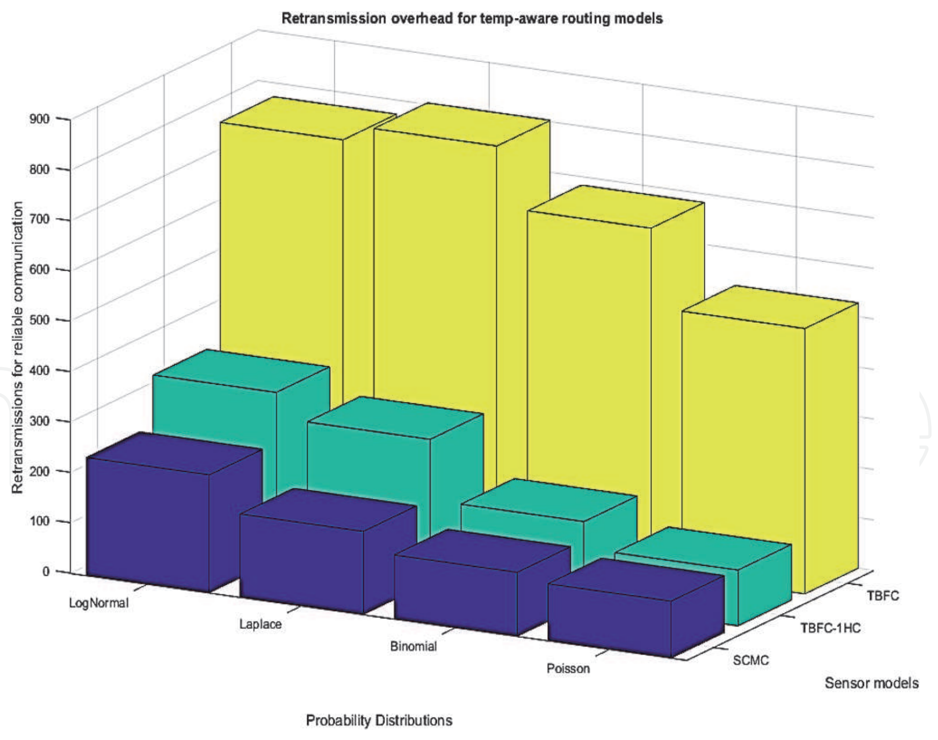

Figure 2.
Number of retransmitted packets in unit time for the three models.

8. Energy saving and network lifetime improvement for IoT-HSNs

A key question related to IoT-HSNs entails the energy-fidelity trade-off. When sensor data is transmitted after processing and transformation, it is expected that the fidelity level of the received data must be acceptable and appropriate to be useful. Any data transformation and transfer need to be done in an energy efficient manner. This requirement advocates for selective processing of collected physiological data samples.

8.1 Sample reduction with prediction for energy saving

Another major operation and design issue with IoT-HSNs involves improving the lifetime of sensing for sensor nodes and thus that of the networks. The issue is caused due to the constraints on batteries that need to be small in size and cannot pack a lot of power due to this constraint [66, 67]. The sensor nodes collect data samples and relay them to the CSS at an acceptable rate as dictated by the QoS of the physiological parameter. However, the total number of samples collected and transmitted by the sensor does not take the nature and frequency of variations in the physiological parameter into account by default. In this work, an attempt has been made to address the energy-fidelity trade-off [68] by reducing this data content through signal processing techniques. The approach involved selective exclusion of some sample data from transmission. Prediction techniques were used to recreate the missing samples that were not transmitted. The approach used in this work was different from the dual prediction technique proposed by Mishra et al. [69]. Prediction techniques involve approximations that come with errors but if the error is negligible, the recreated signals can be used for an early diagnosis if not for full diagnosis, while the patient is on the way to hospital.

The fidelity of data and the accuracy of information contained would undoubtedly be better if all the data samples sensed by the physiological sensor were transmitted. Although this sampling approach would satisfy the Nyquist criterion, it would result in transmission of several samples which could be predicted with reasonable accuracy using numerical techniques within some range of error. While such data might not truthfully reflect what continuous monitoring would reveal, the medical personnel would still be helped by early diagnosis, planning or determination on the course of action.

The author first reduced the transmitted samples for each of the parameters in the 24-channel IoT-HSNs to half by skipping transmitting alternate samples and tried predicting the skipped samples at the receiving end by using a simple proportional-integral-derivative (PID) scheme and a more computationally involved prediction using non-linear regression involving an artificial neural network (ANN-NLR). The results are shown for a couple of cycles of prediction for the ART parameter in **Figure 3**. The approximation used in the two prediction strategies generates some error, which is still not too big to alter the characteristics of the ART signal appreciably. This error is shown in **Figure 4**.

The amount of data was reduced by periodically skipping those samples from the original set and predicting the missed samples at the receiving end. The bulk of data marked for transmission could be further used by delta encoding to pack more amount of data in every transmission [59].

Sample data sets for the 24-channel IoT-HSN involving critical physiological parameters such as ECG, central venous pressure, pulmonary artery pressure and arterial pressure signals obtained from Physionet [60], were used as the source to progressively cut down samples and create four different subsets of the original sets like the approach used in [70]. For the sample analysis and graphical evaluation, the programs were written in in MATLAB r2020 [71].

Alternate samples of each of the original sample sets were used to create the first subset, every third sample was picked up to create the second, every fourth sample for the third set and every fifth sample for the fourth set. Thus, the sample sizes of these sets were half, one-third, one-fourth, and one-fifth of the original, respectively. The four sets were transmitted and recreation of original by a variety of numerical interpolation algorithms was attempted at the receiving end. The reconstructed sets were compared with the original set of samples with all samples intact, and the error was calculated. **Figure 5** shows the results of the recreation for

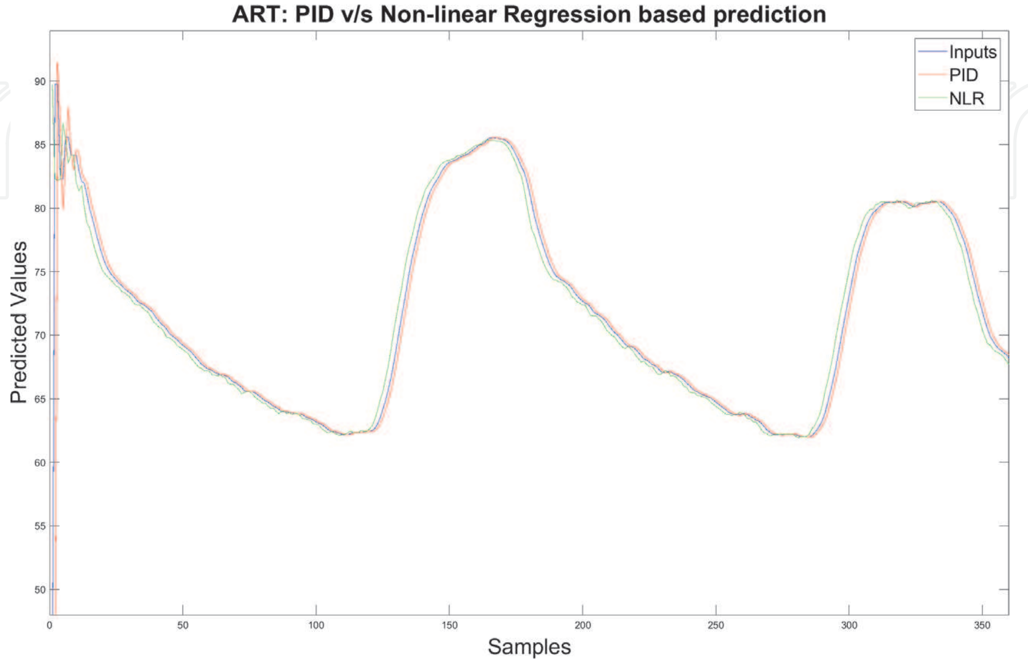

Figure 3.
Plots of comparison of prediction performance by PID and ANN-NLR algorithms for arterial pressure.

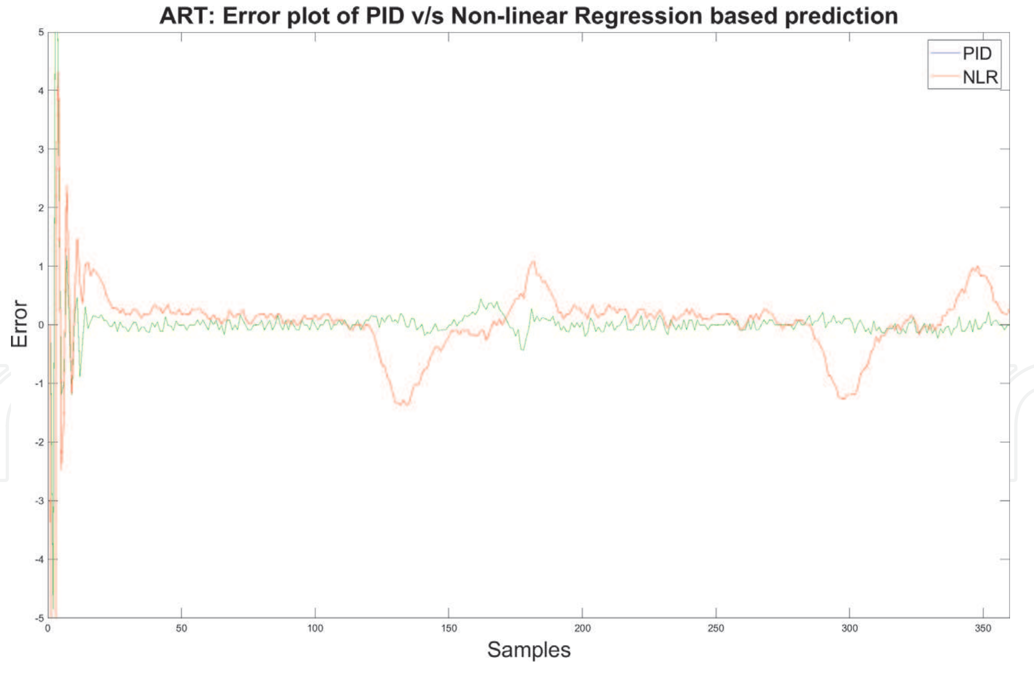

Figure 4.
Error plots of comparison of prediction performance by PID and ANN-NLR algorithms for arterial pressure.

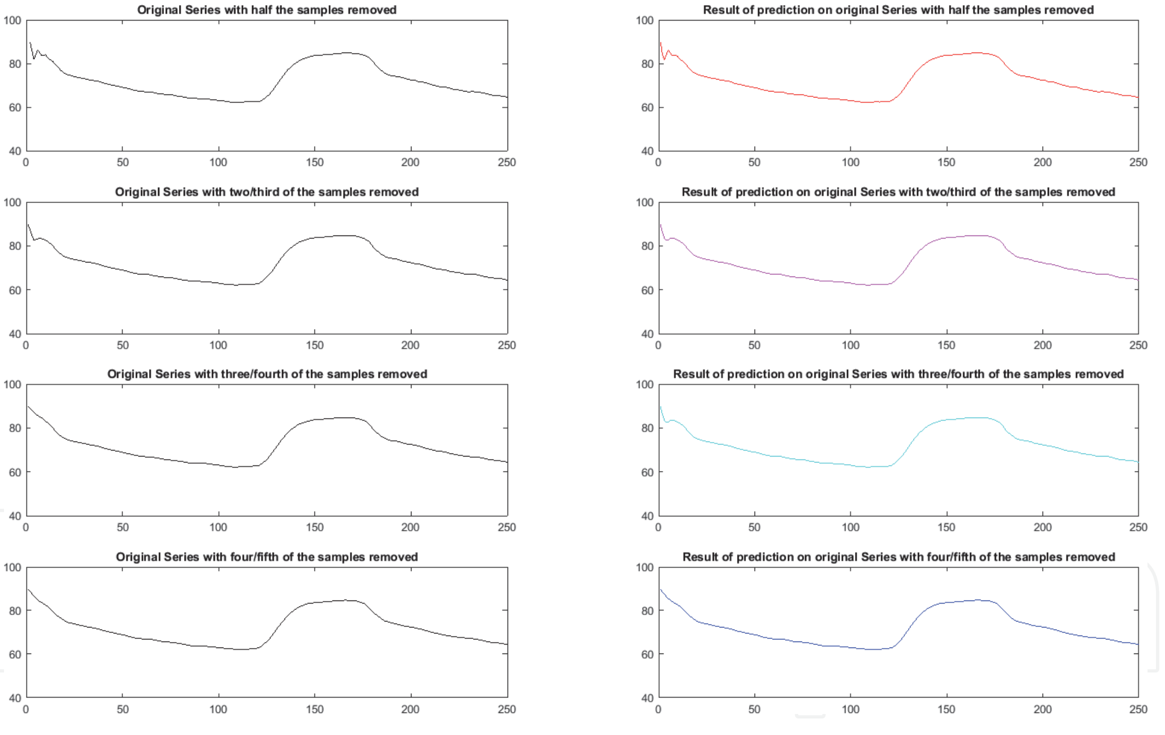

Figure 5.
Prediction of skipped samples for four sample elimination rates through pChip.

the representative ART signal using ANN-NLR prediction after four different rates of sample reductions, with only a few cycles covered for the sake of conciseness. **Figure 6** shows the error in prediction for the four sample reductions. A similar analysis was also done on the other signals of the 24-channel IoT-HSN with comparable results. **Table 1** shows the particulars of the ART signal used as a representative of the results.

The signals recreated at the receiver using five different interpolation techniques over reduced samples for the arterial pressure parameter were compared with the original full sample sets for error in prediction by interpolation. The results of the

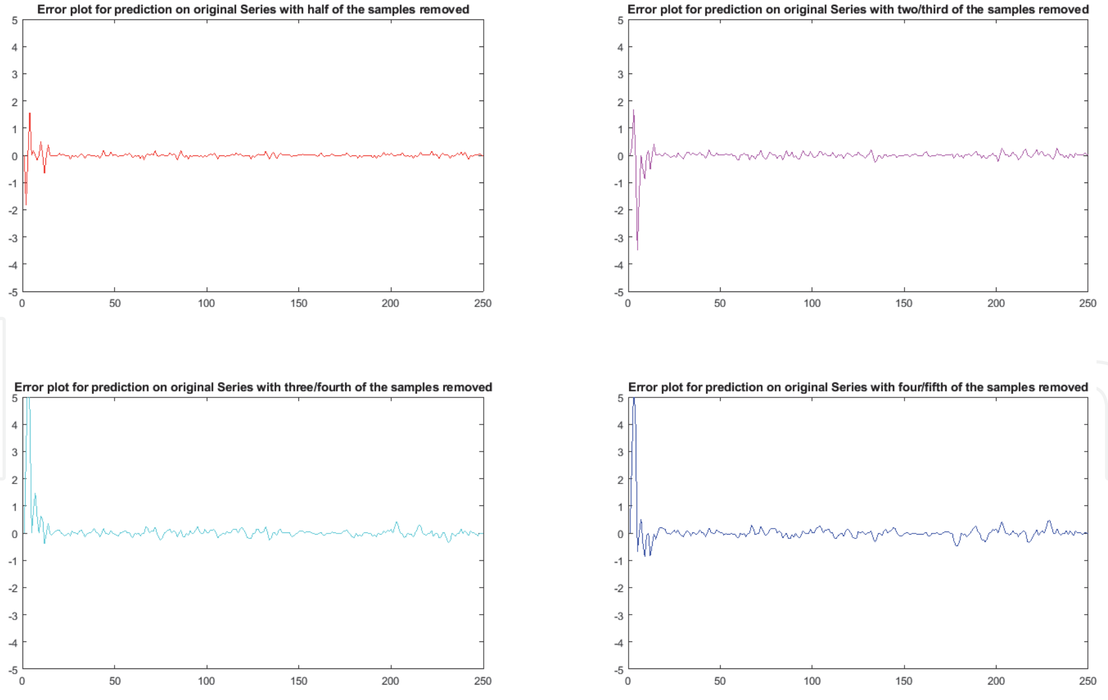

Figure 6.
Error plots for prediction of skipped samples for four sample elimination rates through pChip.

Characteristics	Signal	Signal	Signal
	Minimum	Maximum	Span
ART (mV)	52.35	89.6935	37.343

Table 1.
Signal specifications for the arterial pressure vital sign IoT-HSN parameter.

prediction for the ART signal and the associated error analysis for just the cubic interpolation technique are presented in **Table 2**.

Five numerical interpolation techniques – linear, near, Spline, Pchip and cubic were employed for rebuilding the missing IoT-HSN sample data for the parameters of the 24-channel IoT-HSNs at the receiving end. **Table 3** shows the comparison between the five techniques for the ART parameter.

From **Table 3**, it is evident that the nearest neighbor interpolation algorithm performs the poorest of all but the other four yield lesser error, almost in the same range, with the linear spline interpolation performing better across the sample sets.

Twenty random sets (with 3600 samples transmitted in 10 seconds) of the signals for the 24 channel IoT-HSNs from healthy individuals and patients were employed to assess the performance of the prediction algorithms. The physiological parameters are all different in range, wave-shape, and type of variations. **Figure 3** shows the results of error evaluation after reconstructing the signal using the five interpolation algorithms for one such set of values for the ART signal.

The first column in **Figure 5** illustrates the signal sets with successive reduction in samples. The second column indicates the reconstruction of lost samples for the

1–6 Sample Reduction	Halved	1/3rd	1/4th	1/5th	1/6th
ART (mV)	1.58	1.67	6.01	5.65	1.02
%Error	0.04	0.04	0.16	0.15	1.02

Table 2.
Peak error with sample reduction for arterial pressure using cubic interpolation.

Reduced	Nearest	Linear	Spline	Pchip	Cubic
1/2	0.102	0.043	0.049	0.043	0.034
1/3rd	0.104	0.082	0.039	0.045	0.057
1/4th	0.12	0.166	0.158	0.161	0.162
1/5th	0.212	0.159	0.143	0.152	0.152

Table 3.
Maximum percentage error values for ART from the five numerical interpolation techniques.

corresponding row after data reception done using the Pchip interpolation prediction.

9. Considerations for battery usage in IoT-HSNs

A key requirement of IoT-HSNs is low power wireless which in turn makes signal detection difficult. Low power wireless is required, which makes signal detection more challenging. Common and proven technologies such as Bluetooth, ZigBee, General Packet Radio Service (GPRS) and Wireless Local Area Network (WLAN) might not offer good and optimal solutions to the low power requirement problem.

The growing miniaturization and cost drop on IoT-HSN sensors, circuits and wireless communication electronics is establishing new opportunities for wireless sensor networks in wearable applications. Nevertheless, for sensors to be untethered, the design needs to use wireless communication between nodes along with wireless powering of sensors. This requirement is fulfilled by batteries in most of the portable electronic devices, making them an obvious answer for IoT-HSN wireless applications. However, the batteries have a finite life and require to be replaced or recharged. This limitation presents a cost and convenience penalty which is undesirable in wireless applications including IoT-HSN while the market for such applications and demands grows. One possible solution to this problem involves harvesting energy from the environment for recharging of power sources. Energy scavenging from motion (vibration) and thermal (body heat) sources offer some options for recharging mechanisms that are being investigated. While the power demands of many electronic functions including wireless communication are being actively reduced, energy efficiency of power sources remains a problem because IoT-HSN nodes are intended to operate for a long period of time, especially if they are implanted.

9.1 Batteries and fuel cells for IoT-HSN sensor nodes

Wireless devices can be powered by primary, or rechargeable batteries. Of these, primary batteries are better in energy densities, shorter in leakage rates and lower in cost. The energy density of Lithium-ion batteries that are most used in electronics, is around 700–1400 J/cc for rechargeables [72], and the figure for primary cells is higher. Batteries used for IoT-HSN applications are preferred to last at least a year. A lifetime of 1 year corresponds to 32 J/micro-watt of average power for an average power requirement of some tens of micro-watts.

Hence, a finite battery-life of some tens of microwatt-years is attainable for a battery under 1 cc. Search for better alternatives is on because such batteries require replacement and have issues related to toxicity, safety, and operating temperature range. While ultracapacitors are drawing rising interest for powering electronics as their energy densities are much higher than those of conventional capacitors, the density still are way lower than those of batteries [73].

Hydrocarbon fuels are known to have very high specific energy in the range of 16 kJ/cc for pure methanol [74] or 31 kJ/cc for iso-octane [75]. For miniature electronics, exhaustible sources of energy that use hydrocarbon fuel of some type are also under review, although primarily for greater power levels. Small, micro-machined and only few inches big external combustion heat engines have been built to provide power for portable electronics that can generate up to 200 micro-watts [76]. Such engines have a disadvantage of moving parts and very high temperatures, and hence fuel cells are also being widely investigated for applications involving low power. In the pure methanol-based device used in [74], the electrochemical reaction of methanol with water after passing through a polymer membrane results in oxidation of methanol producing free electrons and protons and generating high power levels of 195 mW/sq.cm.

Miniature fuel cells for implantable sensors as small as 0.5 mm thick can also utilize energy harvesting to provide inexhaustible power up to 4.4 micro-watts/sq. cm if they use body fluids such as oxygen dissolved in blood and glucose as the fuel source [77]. A crucial challenge for such power sources that needs to be addressed is their operational lifetime.

9.2 Challenges related to IoT-HSN power sources

Due to difficulties in changing or recharging batteries in IoT-HSN sensors (some implanted), the management of energy consumption for network longevity and resourceful network operation is an important design consideration. The network design methods utilize a sleep-awake cycle for conserving energy and increasing the network operation time because the power requirement for the communications unit in a sensor node is several orders higher in comparison to the transducer and A/D converter unit in the sensor electronics. The author attempted to assess the lifetime of the proposed IoT-HSN framework created using commercial sensors and power supplies focusing on the period that the sensors would remain powered on.

The sample rate for the ART signals used in the representative evaluation was 360 samples per second with the samples encoded in 8-bits and the more popular 12-bits. The total energy necessary for the operation of a IoT-HSN sensor node varies based on factors such as sleep-awake cycle, inter-sensor distances, the time for which the node stays in a specific mode, as well as a system constant.

Based on Heinzelman's sensor node transceiver model [78], the transmission energy required to transmit a k-bit message to a distance of d can be computed as:

$$E_{Tx}(k,d) = E_{Tx-elec}(k) + E_{Tx-Ampl}(k,d) = E_{Elec} * k + \epsilon k d^2 \tag{1}$$

where,
$E_{Tx-elec}$ is the energy expenditure in the transmission electronics,
$E_{Tx-Ampl}$ is the energy expenditure in the transmission pre-amplifier,
ϵ is an amplification factor.
d is the communication distance between sensors.
Their model has the below assumptions:

$$\begin{gathered} \epsilon = 100pJ/bit/m^2 \\ E_{Rx-elec} = E_{Tx-elec} = E_{Elec} \end{gathered} \tag{2}$$

To receive a k bit message, the energy expended in the receiver is

$$E_{Rx}(k) = E_{Rx-elec}(k) = E_{Elec} * k \tag{3}$$

The energy expended in the transceiver electronics for most sensor nodes is identical for transmission and reception circuitry and in a few tens of nJ/bit.

The energy required for transmitting all the samples (and not skipping any of the 360 samples) while continuously operating for a minute was 8.65 mJ when the samples are encoded in 8-bits and 12.97 mJ when the samples are encoded in 12-bits.

The author attempted to assess the life cycles of wireless networks comprising of two commercially available low-power ultra-compact sensor nodes. The minute-long sensor duty cycle comprises of 10 seconds each of transmission and reception succeeded by 40 seconds of sleep. The author used three sensor modes for this evaluation – the Eco [79], Texas Instruments' TI CC3100 [80] in Direct Sequence Spread Spectrum mode (1DSSS) and the TI CC3100 in Orthogonal Frequency Division Multiplexing mode (54OFDM).

The Eco sensor required a current of 16 mA during transmission, 22 mA during reception and mere 2 μA while sleeping.

The TI CC3100 sensor fared fine in the 1DSSS mode while performing amply better in the 54OFDM mode. The author evaluated the performance of these sensors based on three commercially available batteries that supply 3.0–3.6 volts, 0.5A – the CR2032, CR123A, iXTRA and ER34615. **Table 4** summarizes the battery characteristics and the findings for transmission power requirements of the two sensor nodes without any power management applied.

Table 4 indicates that the innovations in low-power sensor design and battery technology enhance the lifetime of the IoT-HSN network.

If the sample reduction algorithm suggested by the author is used, the sensor, and hence the network lifetime would improve in accordance with the sample chop rate. **Figure 7** shows the network lifetime improvement for the sample chop rates.

9.3 Battery life for models using thermal-aware routing

The author also attempted to evaluate the performance of the three thermal aware routing models for network lifetime with the three batteries that were shortlisted and considered by [56]. Of the battery models evaluated, the model based on ECO sensor nodes running on the 19000 mAH ER34615 battery had the best performance for network lifetime without any power management.

The TBFC thermal-aware routing model was found to offer the poorest economy on the battery power in these evaluations as compared to the other two models for the four probabilistic packet distributions. **Figure 8** shows the battery and network lifetime for the model despite retransmissions using the mentioned battery-sensor combination in the number of hours of operation, in conjunction with the details in the tables.

The three models pave a way for a study towards efficient and intrinsically safe, thermal-aware IoT-HSNs for wearable computing. **Figure 9** shows the improvement for the sample chop rate of 3, if the reduction in samples is used with

Battery →	CR2032	CR2447	CR123A	iXTRA	ER34615
Sensor Node ↓	225 mAH	1000 mAH	1550 mAH	1700 mAH	19000 mAH
ECO (16 mA)	1.76	7.82	12.11	13.28	148.62
TI – DSSS (21 mA)	1.34	5.96	9.23	10.12	113.16
TI – OFDM (9.39 mA)	2.99	13.29	20.63	22.63	252.49

Table 4.
Life in days for the different battery models as per their capacities and node power requirements if continuous power drawn.

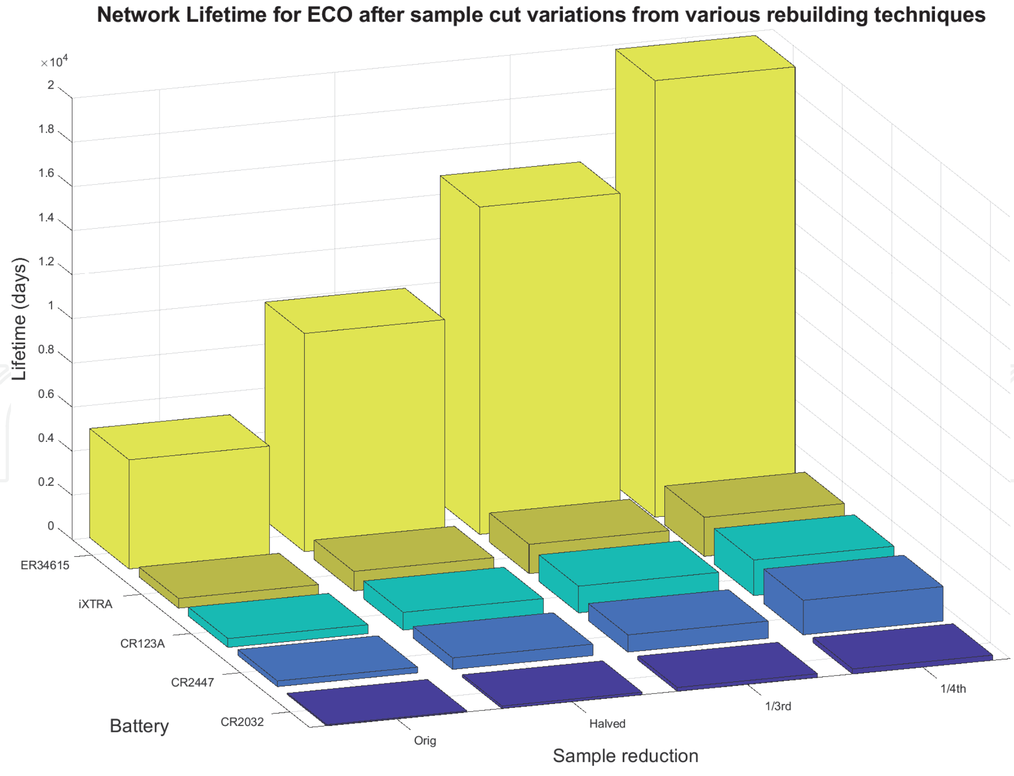

Figure 7.
Comparison plot of battery lives for 5 batteries and four sample rates.

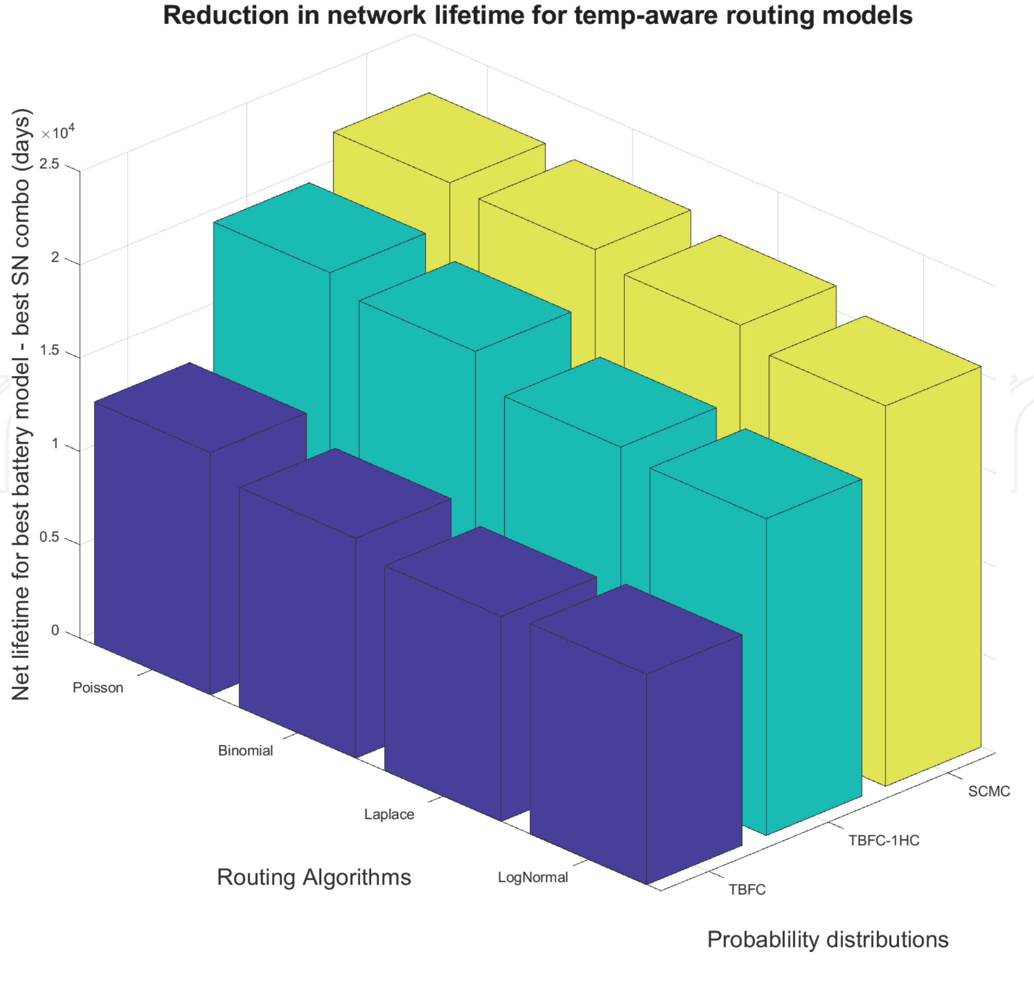

Figure 8.
A comparison of lifetime hours for the three models across four duty cycle distributions.

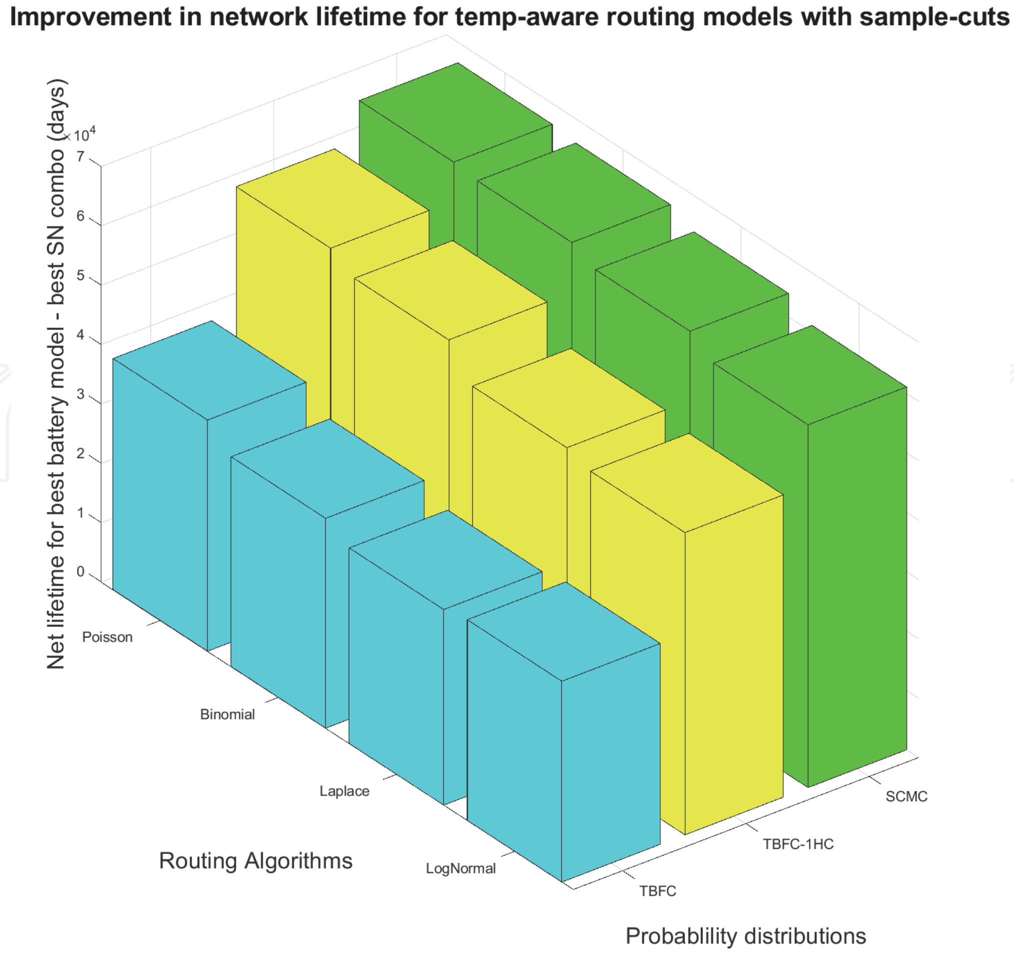

Figure 9.
A comparison of improvement in lifetime hours for the three models for best sensor and battery combination.

prediction for recreating the original signal. This was done for the ECO sensor when used in conjunction with the ER34615 battery, evaluated over the four probability distributions for the three thermal aware routing algorithms. The author's findings indicated that the results were the best for the SCMC routing algorithm with Poisson sample distribution where the sensor and battery combination lasted for almost 66500 hours (7.6 years) with the results for other distributions not very different for the combination. The sensor and network lifetime are seen to be improved in accordance with the sample chop rate.

10. Conclusions

In this article, the author has presented a comprehensive survey of the different types of routing models used for IoT-HSN data. The author has also proposed a thermal and energy aware model that enhances the lifetime of IoT-HSN for intra-network as well as inter-network traffic and evaluated the performance of the model. The author has also demonstrated energy savings by reduction in transmission using a linear elimination algorithm and recreating the missed data at the receiver using a variety of techniques involving a variety of interpolation techniques and prediction using PID and NLR-ANN with very low error values. The savings shown from the model and the enhancement of network lifetime have been demonstrated in quantified as well as graphical forms.

While the basic factors of the network look good for employing energy optimization in IoT-HSN applications, the dynamic execution of the proposed model needs to be studied in better detail for real life HSN applications. An extension of this work could focus on a clinical implementation covering several vital parameters with varying rates of change in them. More possibilities could emerge if the model is tested on well-founded and strong applications such as pacemakers, insulin monitors or movement sensors and prosthetic control.

This article opens the arena for further probing of thermal, QoS and energy aware design of micro-hardware for wearables and implantable bionics. The thermal and energy aware model offers an encouraging prospect to be selected as a design standard for IoT-HSN applications whereas none exists at this time.

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Conflict of interest

The author declares no conflict of interest.

Abbreviations

IoT	Internet of Things
HMI	Human-machine interface
IoT-HSN	IoT healthcare sensor network
MEMS	Micro Electro-mechanical Systems
PDA	Personal digital assistant
WHO	World Health Organization
ART	Arterial pressure
WSN	Wireless sensor network
SMILE	Smart Independent Living for Elders
CSS	Coordinating Sink Station Unit
QoS	Quality of service
SAR	Specific absorption rate
FCC	Federal Communications Commission
ICNIRP	International Commission on Non-Ionizing Radiation Protection
TARA	Temperature Aware Routing Algorithm
LTR	Least Temperature Rise
ALTR	Adaptive Least Temperature Rise
LTRT	Least Total Route Temperature
CDR	Critical Data Routing
MAC	Media Access Control
SCMC	Sensor-Centric Monte-Carlo
TBFC	Tissue-Based Fixed Coordinator
1HC	One-hop caching
EEG	Electroencephalogram
ECG	Electrocardiogram
EMG	Electromyography

BAN	Body area network
SPO2	Peripheral capillary oxygen saturation
PID	Proportional-integral-derivative
ANN-NLR	Artificial neural network – non-linear regression
GPRS	General Packet Radio Service
WLAN	Wireless Local Area Network
TI	Texas Instruments
1DSSS	Direct Sequence Spread Spectrum
54OFDM	Orthogonal Frequency Division Multiplexing

Author details

Amitabh Mishra
University of West Florida, Pensacola, FL, USA

*Address all correspondence to: amishra@uwf.edu

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