A Joint Deep Learning and Internet of Medical Things Driven Framework for Elderly Patients

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ABSTRACT Deep learning (DL) driven cardiac image processing methods manage and monitor the massive medical data collected by the internet of things (IoT) based on wearable devices. A Joint DL and IoT platform are known as Deep-IoMT that extracts the accurate cardiac image data from noisy conventional devices and tools. Besides, smart and dynamic technological trends have caught the attention of every corner such as, healthcare, which is possible through portable and lightweight sensor-enabled devices. Tiny size and resource-constrained nature restrict them to perform several tasks at a time. Thus, energy drain, limited battery lifetime, and high packet loss ratio (PLR) are the keys challenges to be tackled carefully for ubiquitous medical care. Sustainability (i.e., longer battery lifetime), energy efficiency, and reliability are the vital ingredients for wearable devices to empower a cost-effective and pervasive healthcare environment. Thus, the key contribution of this paper is the sixth fold. First, a novel self-adaptive power control-based enhanced efficient-aware approach (EEA) is proposed to reduce energy consumption and enhance the battery lifetime and reliability. The proposed EEA and conventional constant TPC are evaluated by adopting real-time data traces of static (i.e., sitting) and dynamic (i.e., cycling) activities and cardiac images. Second, a novel joint DL-IoMT framework is proposed for the cardiac image processing of remote elderly patients. Third, DL driven layered architecture for IoMT is proposed. Forth, the battery model for IoMT is proposed by adopting the features of a wireless channel and body postures. Fifth, network performance is optimized by introducing sustainability, energy drain, and PLR and average threshold RSSI indicators. Sixth, a Use-case for cardiac image-enabled elderly patient's monitoring is proposed. Finally, it is revealed through experimental results in MATLAB that the proposed EEA scheme performs better than the constant TPC by enhancing energy efficiency, sustainability, and reliability during data transmission for elderly healthcare.

INDEX TERMS Deep learning, elderly healthcare, cost-effective, intelligent systems, IoMT, reliability.

I. INTRODUCTION

Cutting edge technologies such as deep learning (DL) and the internet of things (IoT) trend bring revolution in cardiac

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image-driven elderly patient monitoring. The cardiac image processing approaches, in association with the IoT driven portable devices, are promoting emerging and supportive real-time healthcare platforms at remote locations. In the meantime, electronics and wireless communication technologies have entirely reshaped the medical world by promoting
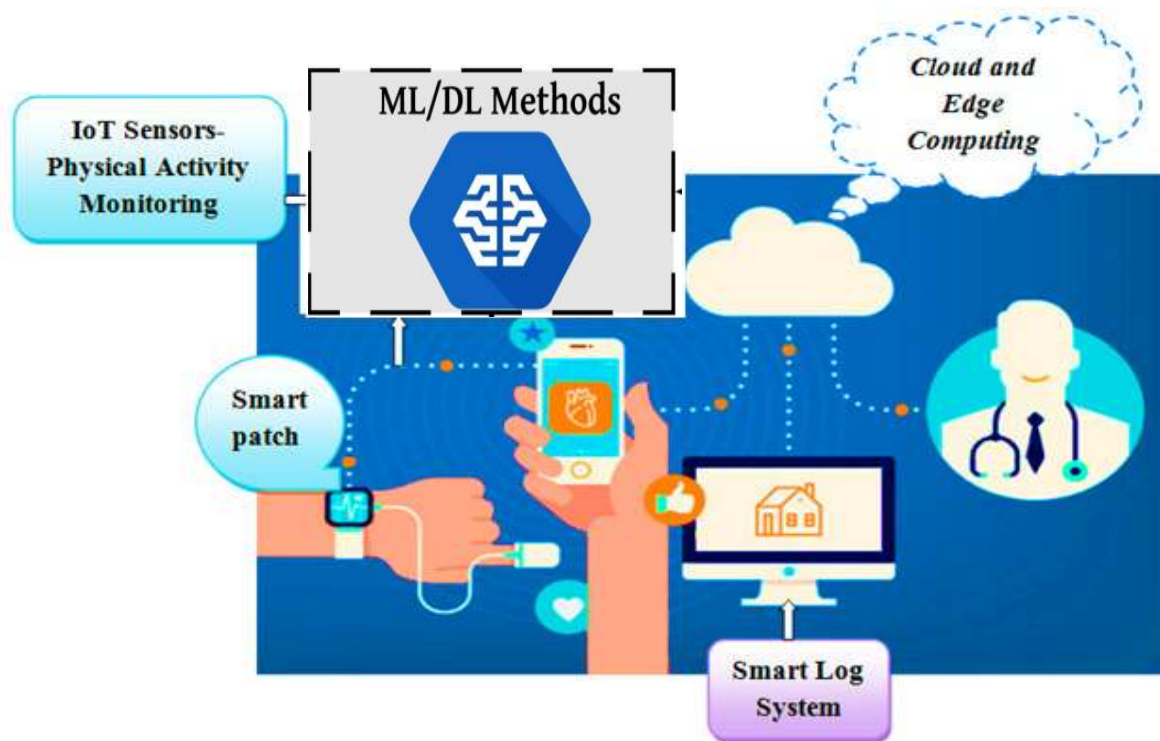
FIGURE 1. Smart and sustainable healthcare based on Cardiac image analysis to help the patients and physicians.

intelligent and small sensors that can be used on or in the human body. The integration of these sensors with emerging healthcare technologies is the paradigm shift towards high sustainable, smart, and pervasive medical cities and homes to serve the elderly patients at remote locations [1], [2]. Body Sensor Networks (BSNs) is an instrumental and potential candidate to increase the research and development in the medical sector for further improving the healthcare platform. Besides, BSNs comprise a large number of heterogeneous biological sensors, and these sensing nodes measure and wirelessly transmit the abnormal changes in a patient's vital sign or physiological signals such as temperature, heart-beat, and brain signals blood pressure, as shown in Fig. 1. We explain the architecture of BSN based smart and sustain-able healthcare in which wearable sensors sense the date and transmit the data through the wireless channel to the base station (BS). Further, it is sent to the eHealth care centers where data servers are present and can be accessed to diag-nose and monitor the patients. At present, it is essential to provide high-quality healthcare facilities due to the increase in population, chronic diseases, and health un-aware tips. Cardiac images, IoMT, DL based applications to the health-care industry are rapidly evolving due to state-of-the-art tech-nological trends and practices. Besides they provide ease and comfort with 24-hours medical facilities to everyone without any constraint on his/her normal daily life routine. How-ever, due to small size, lightweight, and power-constrained nature, these devices face one of the severe problems of battery charge drain and hence, the shorter lifetime and less

energy efficiency. Many researchers have proposed distinct techniques/methods for energy optimization and battery life-time extension, e.g., medium access control (MAC), physical layer, network topology-oriented, and transmission power control (TPC). But smart and sustainable healthcare platform is still the cornerstone to be developed.

Main contributions of this research are:

- First, a novel self-adaptive power control-based enhanced energy-aware approach (EEA) is proposed to reduce energy consumption and enhance the battery lifetime and reliability. Proposed EEA and conventional constant TPC are evaluated by adopting real-time data traces of static (i.e., sitting) and dynamic (i.e., cycling) activities and cardiac images.
- Second, a novel joint DL-IoMT framework is proposed for cardiac image-driven remote elderly patients.
- Third, DL driven layered architecture for IoMT is pro-posed, this helps in analyzing the medical image pro-cessing mechanism
- Forth, Battery model for IoMT is proposed by adopting the features of the wireless channel and body postures
- Fifth, network performance is optimized by introduc-ing sustainability, energy drain, and PLR and average threshold RSSI indicators.
- Sixth, a Use-case for cardiac image-enabled elderly patient's monitoring is proposed.

The rest of the sections are arranged as follows. Section II presents detailed related works. A novel joint DL-IoMT

framework is proposed in Section III. Dynamic wireless channel modelling is addressed in Section IV. System architecture with detailed functionality is presented in Section V. DL driven layered architecture for IoMT is proposed in section VI. Section VII proposes a battery model for IoMT. Section VIII proposes a novel energy-efficient algorithm. Experimental results are discussed in Section IX. Finally, Section X concludes the paper.

II. EXISTING WORKS

Most relevant research work is presented. Gao *et al.* [1], propose an energy-saving scheme for medical images through capsule endoscopy in BANs, which control energy consumption by adaptively adjusting the transmission power, but they do not consider other parameters like reliability and latency, etc. Besides, their work does not consider the received signal strength indicator (RSSI) for system performance examination. The adaptive TPC algorithm for energy saving in medical image-based health monitoring systems, where they used real-time channel datasets and analyzed that dynamic nature of wireless link impacts a lot on the energy and reliability but their proposed adaptive TPC method saves more energy by compromising reliability for healthcare applications [2]. While due to the sensitive nature of the medical information, it is important to develop a reliable, sustainable, and delay-tolerant methodology. In [3], Obaidat *et al.* examine WBAN performance by capturing the packet reception ratio (PRR) and its concurrence with RSSI by building performance benchmarking in resources management. In healthcare, it is essential to analyze static on-body channel characterization and link quality for 2.4 GHz medical healthcare platforms [4]. Cheour *et al.* present an overview of the routing protocols and power management techniques for global and local systems [5]. Sodhro *et al.* present various power-efficient and battery charge optimization strategies during media transmission with a novel framework of heart-attack patients but has not been considered the TPC-enabled strategy [6].

Energy saving is the cornerstone of a sustainable and smart healthcare system by adopting TPC-driven techniques [7], [8]. The adaptive energy-saving mechanism has more advantages than traditional methods in medical applications. Besides, it is tested on real-time datasets with dynamic TP levels [9]. Xiao *et al.* develop novel TCP algorithms with vast experimental set-up for energy saving in BANs [10]. A unique technique for the telemedicine system, which optimizes the medical-QoS could be useful in different medical scenarios [11]. Won *et al.* present TPC based energy saving technique in wireless networks [12]. The introduction of the notion of energy-aware and battery lifetime extension approach for wearable devices during media transmission in WBSNs plays a significant role [13], [14]. Sodhro *et al.* develop the battery-friendly strategy for charge optimization in wireless-capsule endoscopy. All the aforementioned researchers mostly focus on the energy-saving techniques by different methods in wireless system, WBAN, and WSN, but
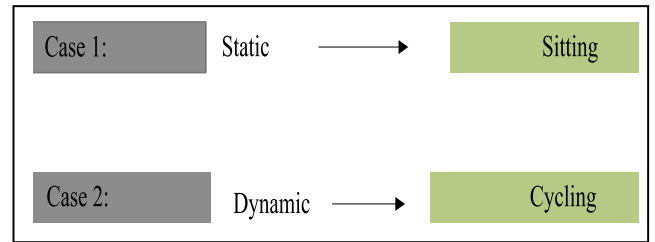

FIGURE 2. Static and dynamic body postures.

very few focus on the energy optimization by using TCP, if they use TPC approached, but oversimplified to consider the real-time channel datasets for static and dynamic body postures with network metrics such as, standard deviation, packet loss ratio (PLR), and RSSI [15]. Chenfu *et al.* develop a novel energy-saving mechanism in transmission merely for internal circuitry but does not work for other parts of transceiver [16]. An innovative framework is proposed in [17]; it is based on four different methods and algorithms that jointly adjust the TPC and duty-cycle of the BSNs to optimize energy consumption. This framework is evaluated through Monte Carlo simulation, and this paper claim that this framework saves more energy at acceptable PLR due to its self-adaptive nature. Youming *et al.* design a scheduling strategy based on a game hierarchy for resource allocation in wireless communication [18]. However, two different algorithms for IoT based smart cities are stated in [19]. The first algorithm adaptively adjusts the bandwidth and power of the tiny nodes by the hybrid approach to optimize the energy consumption. In contrast, the Second algorithm controls the delay during the transmission of media. Moreover, tanwar *et al.* devise an IoT based smart home for elderly citizens [20]. Along with power-efficient communication in IoT, researchers across the globe have highlighted that medical data processing, data security, development of smart home automation systems are also key concerns for IoT [21]–[26].

III. PROPOSED DEEP-IOMT FRAMEWORK

The proposed framework comprises three essential parts, first, cardiac image and vital sign signal data analytics: which contains several wearable devices, i.e., edge devices, mobile cell phones, sensor nodes. Second, deep learning (DL), which is the key supporting role in examining the features and classes of the data in correlation to the internet of medical things (IoMT) networks. Third, IoMT is a medical healthcare platform with key focus on pervasive and smart healthcare (see figure 4). IoMT is the network of wearable devices for classifying the data patterns by focusing on error estimation. Because DL techniques are intelligent and adaptive techniques for identifying distinctive and promising data types. IoT-devices for wearable healthcare are the key role players for data examining and human nerve systems such as vital sign signals, etc. So, cardiac images and collected big data analytics, IoT and other DL are the key factors for wise and intelligent decision making.
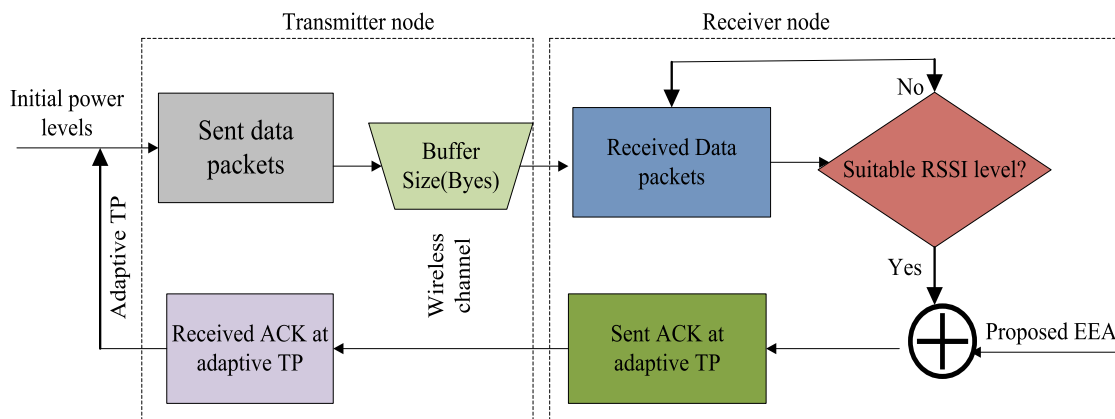
FIGURE 3. TPC mechanism in proposed EEA.

IV. WIRELESS CHANNEL FEATURES

The performance of wireless links is examined by properly evaluating the received signal strength, which is the main parameter for analyzing the cardiac image data quality to exploit the stability and reliability of the medical system. It is computed by taking an average of the incoming data packets by adopting sitting and cycling body features. RSSI is associated with the transmission power (TP) and distance, while here only TP is considered with a minimum **FIGURE 2. Body Posture detection in smart health-care systems** and maximum levels of -25dBm, and 0dBm, respectively.

It is assumed that if its value is -100 dBm then the packet will be dropped, which shows the worst channel condition, and if -88 dBm threshold is adopted then better link quality will be obtained. In this experimental set-up real-time datasets of cardiac images and body postures from NICTA [2], [25] are considered, which support in measuring the path-loss and data analysis of static and dynamic body postures respectively. High frequency, for instance, 2.4 GHz promotes the large PLR, unlike the low-frequency band. Besides, sitting and cycling body postures needs different frequency and hence the PLR with less and more quantity, as shown in Figure 2. In other words, it can be claimed that channel features efficiently characterize the power and reliability requirements.

V. SYSTEM BLOCK DIAGRAM

Transmitter nodes generate the cardiac image and body posture data packets in the periodic fashion by storing in buffer size, then transferred to the receiver node. Aggregated RSSI will be estimated by considering the transmission power requirement. After the short inter-frame space period (*pSIFS*), the receiver node forwards the acknowledgment (ACK) to the transmitter node. We assumed that all the packets are transmitted successfully at the receiver node, as shown in Fig.3.

VI. PROPOSED DL DRIVEN LAYERED ARCHITECTURE FOR IOMT

In IoMT there is the continuous transmission of media like medical imaging, capsule endoscopy data among patients and doctors; more charges are consumed. The main challenge for the recent emerging and innovative digital imaging world is the heterogeneous technological platform without a stable communication/content delivery environment. Also, lack of high interoperability among heterogeneous technological trends there are chances of less throughput and delay while transferring medical imaging information. For instance, IoT driven sensor devices are considering as the paradigm shift to transform the landscape of the medical imaging from patients' homes to hospitals. Also, feedback from physicians, patients, and medical staff/nurses will be transferred consequently for proper examination and monitoring of the critical events. The pervasive and smart medical platform is revolutionized by device to device (D2D) communication. IoT enabled internet of healthcare vehicles (IoHVs) are the backbone of the ubiquitous medical-care in urban and rural areas to facilitate the end-users. These portable devices, on the one hand, made convenience to the medical world while, on the other hand consume more battery charge and power, thus shorter battery lifetime. It is necessary to develop the power and battery-charge aware methods in IoMT for facilitating the aging society at the cost-effective rates while medical imaging and media streaming contents are vital indicators for presenting a better and clear picture of the emergency patients.

This section proposes the layered framework of IoMT, which is illustrated in Figs 5 (a) and (b). The proposed DL driven layered structure comprises four layers. The detailed explanation of the layers is as followed.

Layer 1: This layer defines the patient having wearable devices attached to the human body. The wearable devices take medical data like ECG, temperature, EEG, etc of the patient. Even if the patient is in motion or sleeping, if the medical condition becomes ill, then measures the data.
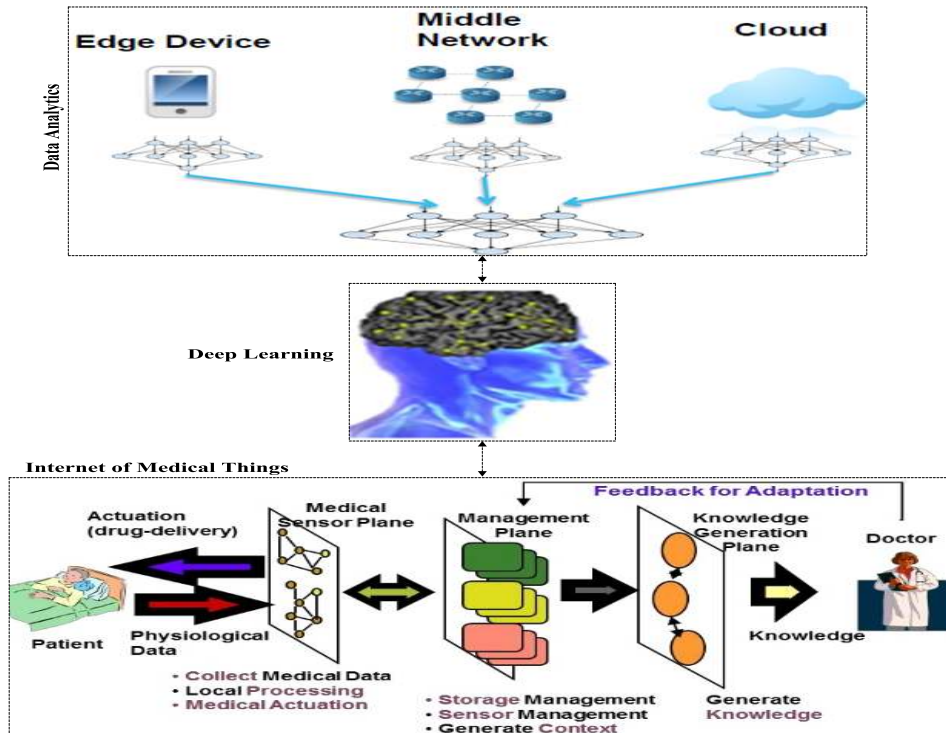
FIGURE 4. Proposed Framework of Deep-IoMT: Three layers are presented layer1, data analytics through IoT based wearable devices, layer 2, shows DL mechanism, layer3, addresses IoMT platform.

Layer 2: This layer defines the connectivity means how communication will occur. The patient can send the data to the doctor through Wi-Fi, Zigbee connections. The connectivity must be reliable so that the data should be transfer properly. If the link lost, then it produces a delay in the treatment of the patient.

Layer 3: Rapid proliferation in IoMT devices are playing a remarkable role in collecting medical image data because desktop computers are not efficient and accurate for data collection, clustering, and analysis. Besides, there are more chances to get unfiltered and raw data. The medical cloud for storing the patient's data/information is one of the emerging healthcare entities for emergency content backup. That information will be used by physicians and hospital staff for predicting future medical image related diseases. So, this layer connects the patent data with doctors so that doctors can saw that information and give proper treatment.

Layer 4: This layer defines the doctor's side or hospitals where a doctor can have access to the patient medical data. The doctors can have access to patient records.

The proposed battery model enhances the battery lifetime of low power sensors in IoMT. The proposed algorithm improves the battery lifetime by taking the recovery effect of the battery into concern is a battery-aware method. The recovery effect of battery is the process of giving some idle time to the battery so that the remaining charges can be utilized. The system model further explains the details of model.

VII. PROPOSED BATTERY MODEL FOR IOMT

The human physiological signal, such as an electrocardiogram (ECG), blood pressure (BP), temperature, etc transmission through wearable devices, is the emerging trend in today's pervasive healthcare sector. The critical challenge is to optimize the battery charge, power drain and hence the lifetime of IoT driven portable devices because due to the small size and resource-limited nature of handheld devices, frequent replacement and recharging of the battery is a cumbersome task. Besides, the discharging process of battery is non-linear. There are two factors in battery behavior one is rate capacity effect, and the second one is the recovery effect. The rate capacity effect is the maximum capacity of battery supplied to load like 1C means battery gives 1-hour capacity of charges. The C-rate is inverse relation with time 2C with half-hour time discharge. Fig.6 shows the C-rate versus the percentage of capacity.

Rakjmatov presented an analytical battery method which is based on the electrochemical reactions and equation of diffusion having following mathematical expression as in eqs.(1) and (2)

$$\alpha = \int_0^L i(t)dt + \int_0^L i(t)\left(2\sum_{m=1}^{+\infty} e^{-\beta^2 m^2(L-t)}\right)dt \qquad (1)$$
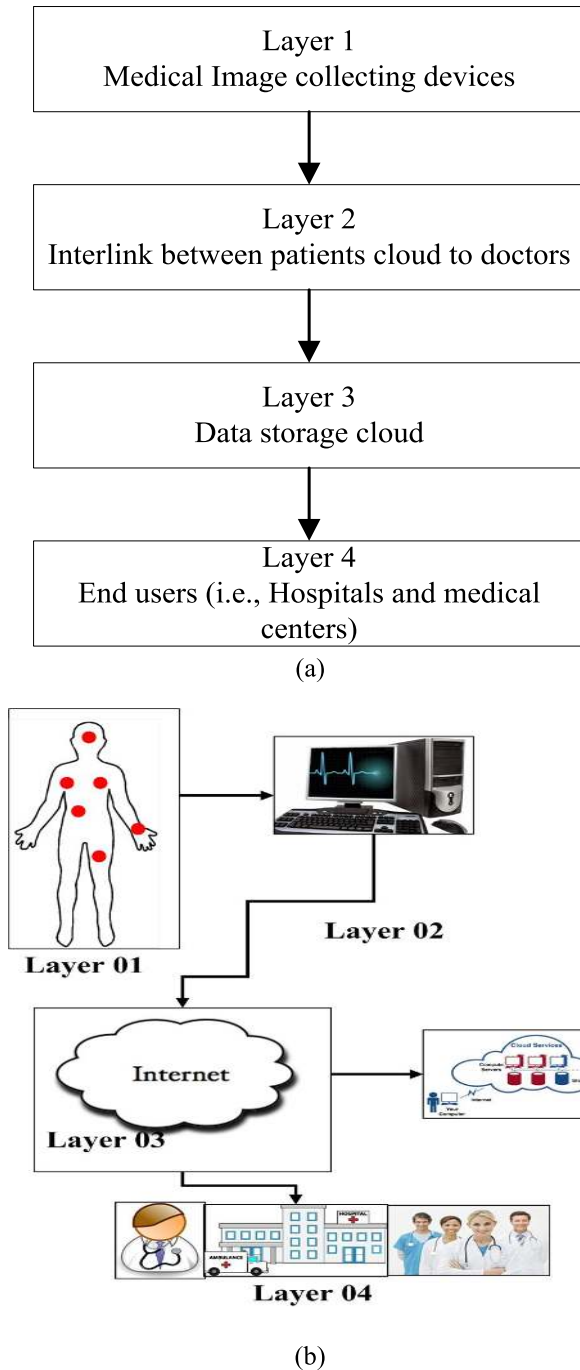
(a)

(b)

FIGURE 5. a) Layered Architecture, b) Working principle of Layered Architecture.

Whereas, α, β, $i(t)$ and L presents battery storage, non-linear functionality of battery, Current profile (mA) and lifetime of battery respectively. For easy understanding and analysis above equation is transformed into a discrete equation. Considering the load current formed into a series of current values $I_1, I_2, \dots, I_N$ whereby I_k denotes the current for the kth task at duration t_k with inter-arrival period $\Delta k = t_{k+1} - 1$. In addition, battery cost function $\sigma(t)$ over time t properly explains its features for computing charge drain as shown in
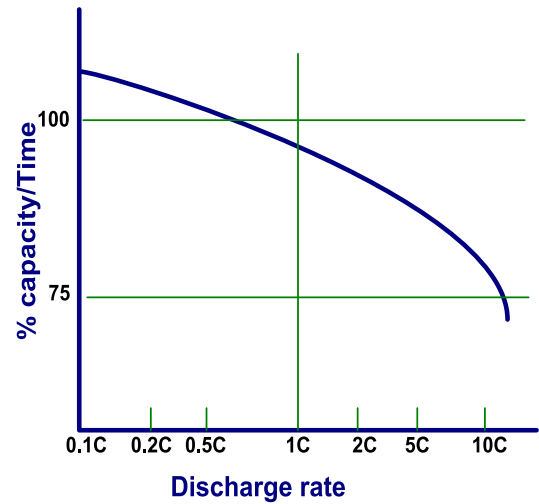

FIGURE 6. Battery rate capacity effect.

eq.(2).

$$\sigma(t) = \sum_{k=1}^{M} I_k \Delta_k + \sum_{k=1}^{M} 2I_k \sum_{m=1}^{\infty} \frac{e^{-\beta^2 m^2} \left(e^{-\beta^2 m^2 \Delta_k - 1}\right)}{\beta^2 m^2} e^{-\beta^2 m^2 t_k}$$

(2)

The two key parts of battery model are linear $l(t)$ and non-linear, and non-negative unavailable $u(t)$ which are used fully and partly while transferring medical images to and from hospitals. If the idle time slot is introduced in the beginning, then unused charge will be converted into available charge amount with the help of charge recovery principle. If the continuous functioning of the battery is being analyzed, then lifetime L is considered. If the unavailable charge amount exceeds the actual stored quantity, then it is difficult to obtain the charged battery status back. Due to the diffusion mechanism of Li-ion battery non-linear discharging process is achieved, and thus entire charge amount cannot be transferred to the load. During discharge process charges that are attached to electrodes of batteries consumed first and continuously replacing other, which far away from electrodes, and this process continues till all charges of electrodes depleted completely.

The remaining costs which are far away from electrodes remain as unusable and not reach to the surface of the batteries (electrodes of batteries). The idle required to recover these unusable charges is known as recovery effect. The process of recovery effect is explained in Fig. 6. The battery is able to consume energy due to the active elements attached to electrodes of the battery. When all the dynamic elements close to electrodes are depleted, and the remaining charges which left in the battery are diffused, besides battery cannot supply power to load because there is no active element attached to electrodes of battery and battery will sleep. If idle time will be given the active components move towards electrodes of battery for supplying maximum power until active participation of all involved entities. The lifetime of the battery can be extended by adequately following the recovery

effect, which remarkably extends lifetime, unlike traditional methods. The different types of medical imaging sensors on/in or implanted to human body collects proper health data for examining and monitoring emergency events such as brain tumor, and endoscopy in IoMT. These implanted sensors are Li-ion battery-powered systems with tiny size, lightweight, less computationally complex and smaller charge storage capacity [8]. The various research works are carried-out on battery charge drain optimization and lifetime extension of the entire network by focusing on decreasing the consumption of energy of the battery [18]. Self-recovery is the effect of Li-ion battery that means when some period of idle time given to them, then the unusable charges can be utilized or transferred into available charge [18]. We can prolong the working time of battery and node by properly scheduling the recovery time [18]. The recovery effect of the battery is modeled as a finite state machine as it continues its state to recover the available charges. The state transition depends on the input voltage levels given to the system.

VIII. PROPOSED ENHENCED ENERGY-AWARE APPROACH

We propose a novel TPC driven enhanced energy-aware algorithm (EEA) for cardiac image-based elderly patient monitoring systems. It adopts the transmitter power levels by considering the ACK from the receiver node and temporal variations in wireless channels. Proposed EEA is a reorientation of the adaptive power control algorithm [2], but both use different strategies of power allocation. Key components of proposed EEA are lowest (i.e., initial/first valued) and latest (last/second) RSSI samples as shown in Fig. 7. The proposed EEA considers both the lowest and latest samples due to the dynamic wireless channel and its adaptive power allocation mechanism. Weighted average RSSI and threshold RSSI are denoted as $\overline{RSSI}$, and respectively. While $RSSI_{th}$ functions in-between lower and higher variable threshold TRL, TRH_{var} accordingly. Wireless channel performance is categorized by assigning weights such as α_1 (i.e., good quality), and α_2 (i.e., bad quality). Besides, change in TP level, path loss, and distance between transmitter and receiver nodes, RSSI deviation, interference and fading are depicted as, ΔP, PL, d, ΔS, I, Fa accordingly. Eq.(3) computes the aggregate value of RSSI by considering various entities which are affecting the reliability of the wireless channel and hence the energy drain and battery lifetime of sensor nodes. Eq.(4), allocates power level according to the need of the receiver nodes by using the channel coefficients, targeted RSSI, path loss and RSSI variation according to the distance between transmitter and receiver nodes. Power levels will be adapted by using eq.(5), according to the fluctuation in the wireless channel, deviation in RSSI value, and requirement of the receiver.

$$\overline{RSSI(n)} = \frac{\Delta P \times PL \times d^{-\alpha_i}}{\Delta + \sum_{i=0}^{n} RSSI_i + I + Fa} \quad (3)$$
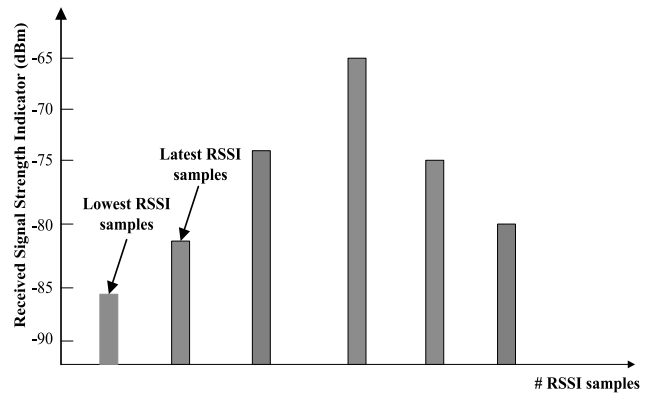
FIGURE 7. RSSI samples.

A higher threshold with dynamic features is calculated by considering the fixed lower threshold and RSSI variation, as in eq.(4). Deviation in RSSI can be calculated in eq. (7) by considering total RSSI samples, lower and higher thresholds.

$$P_i \leq \Delta P + THR_{var} \times (RSSI_{th} - TRL) + \alpha_1\alpha_2 \leq P_{i+1} + \Delta \quad (4)$$

$$\Delta P = \frac{THR_{var} \times (RSSI_{th} - RSSI_i) + \alpha_1 \times \alpha_2 \leq P_{i+1} \pm \Delta}{(P_i + RSSI_i) - \alpha_1 \times \alpha_2} \quad (5)$$

$$TRH_{var} = RSSI_{th} - TRL \pm \Delta \quad (6)$$

$$\Delta = \sqrt{\sum_{i=1}^{n} (RSSI_{th} - (TRH_{var} + TRL) \times 3\sigma}$$
$$i = 1, 2, \ldots, n \quad (7)$$

Whereby, Δ is the variation in RSSI (dBm), which is calculated for number of RSSI samples (n), $RSSI_{th}$ (-83dBm), TRH_{var} (-85dBm)and TRL (-88dBm) as shown in (5).

Sustainable and smart elderly healthcare is essential in today's medical world. Lowest RSSI samples always help to recall the lost latest RSSI samples in the form of ACK from the receiver. Typical constant TPC has more reliability than the proposed EEA because it adopts the values of RSSI threshold dynamically. One of the drawbacks of constant TPC is that its power adaptation mechanism is constant and complex, which is not appropriate for emergency and delay-tolerant healthcare applications.

IX. EXPERIMENTAL RESULTS AND DISCUSSION

Experimental results of proposed EEA and constant TPC are revealed by adopting real-time cardiac image datasets from NICTA [21] with the average values of RSSI and TP are considered with static and dynamic body features, i.e., sitting and cycling. We adopted 0.5 km/h and 1.5 km/h for sitting and cycling by assuming the confined mobility of elderly patients. The data packets are transmitted with a specific TP level every second, while the RSSI values of the transmitted signal are recorded at the receiver. During the static and dynamic body features, less and more power is drained, respectively,
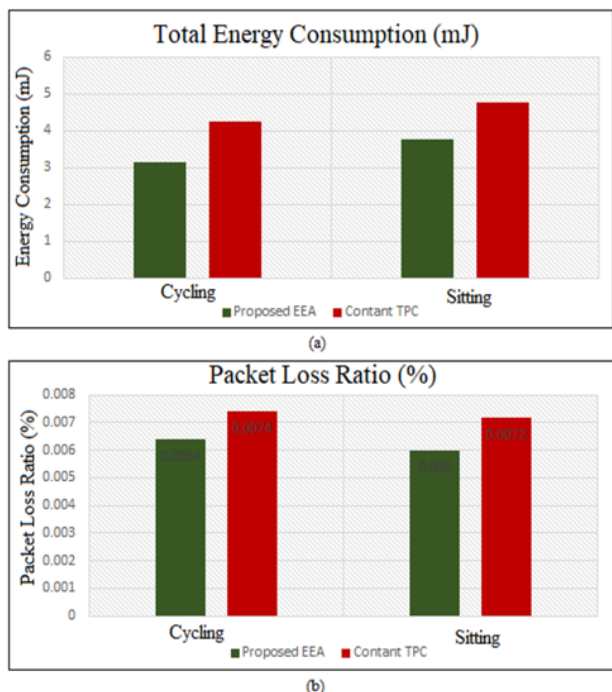
FIGURE 8. The tradeoff between body postures and a) Energy drain, b) Packet Loss Ratio.
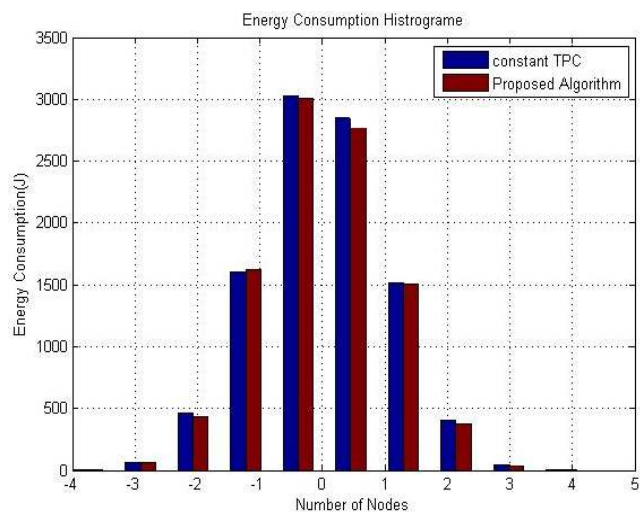

FIGURE 9. Histogram of proposed EEA and constant TPC.

TABLE 1. Simulation entities.

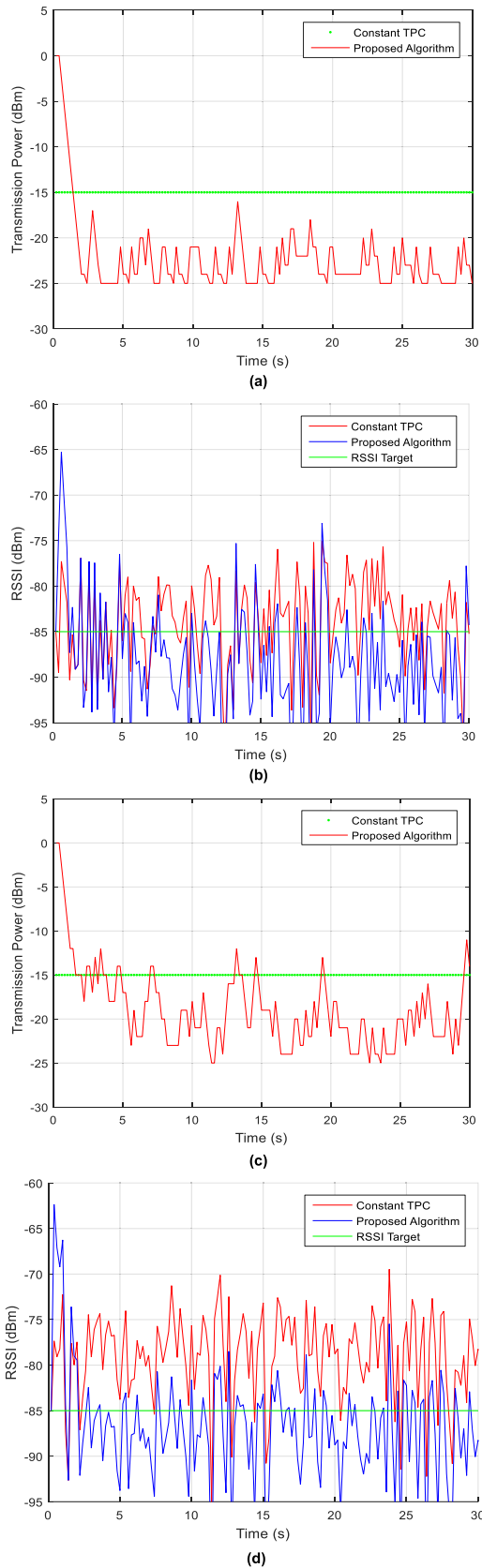| Algorithm	Network metrics	Static and Dynamic Body Traits	
		Sitting	Cycling
Constant TPC	Energy optimization(mJ)	0.0072	0.0074
	Average RSSI (dBm)	-81.53	-82.11
	Battery lifetime (h)	5	4.5
	Packet_loss ratio (%)	4.23	4.78
Proposed EEA	Energy optimization (mJ)	0.0062	0.0064
	Average RSSI (dBm)	-77.13	-80.52
	Battery lifetime (h)	6	5.5
	Packet_loss ratio (%)	3.16	3.75

accordingly. Sustainability and reliability are also affected by more energy dissipation and PLR, and it vital to tackle these for smart and pervasive healthcare. Fig. 9 presents the histogram of proposed EEA and typical constant TPC method. It is analyzed that former consumes less energy than the later while increasing number of sensor nodes. Figure 10 presents the received RSSI values with associated TP levels at a specific time interval for proposed EEA and constant TPC method by considering static and dynamic body postures.

Figure 10 (a), (c) reveals the power consumption by proposed EEA and constant TPC by adopting the static and dynamic features. It can be seen clearly that the proposed EEA keeps TP level lower about −21dBm than the constant TPC method, which consumes more TP about −15dBm. Experimental results show that constant TPC non-linear relationship between power drain and PLR, unlike the proposed EEA, saves more energy with acceptable PLR for smart and sustainable healthcare applications. The extracted results reveal that the proposed EEA is the potential candidate for the intelligent and sustainable pervasive healthcare platform.

On the contrary constant TPC does not follow the features of wireless channel so consumes more power with less PLR and vice versa. In other words, it can be said that conventional constant TPC is not appropriate for emergency and delay-oriented medical applications. Thus, the power levels must fairly be allocated whenever it is found that RSSI is below the lower threshold. In that situation, constant TPC method increases TP needlessly without involving the channel behavior. Hence, proposed algorithm reduces the PLR with more energy-saving at both sitting and cycling postures.

Moreover, proposed EEA adopts varying higher thresholds to adapt the RSSI and hence the channel fluctuation. Figure 10 (b) and (d) revealed the RSSI values of −87dBm, and 90dBm for constant TPC and proposed EEA, respectively. The results show that that proposed EEA shows a stable RSSI level, with acceptable PLR level unlike its counterpart i.e., constant TPC method with less stable RSSI level and less

due to the deviation in the wireless link. Generally, it is observed that dynamic body posture gives slightly higher RSSI deviation and PLR than the static one. Body features are related to the channel characteristics, which impacts a lot to the performance of proposed EEA and conventional TPC methods. Figure 8 (a), (b) presents the entire energy drain and PLR during sitting and cycling scenarios for both proposed EEA and constant TPC, respectively. It is analyzed that there are more power drain and PLR in cycling, unlike the sitting. Also, it is examined that more power drain and less PLR and vice versa are achieved by constant TPC and proposed EEA

FIGURE 10. Transmission power (a), (c), and RSSI (b), (d) for static (a), (b), dynamic (c), (d) body postures.

TABLE 2. Experimental analysis.

Parameter	Value
TRHvar	-85 dBm
Fading (Fa)	10 dB
TRL	-88dBm
RSSI$_{th}$	-83dBm
Carrier frequency	2.4GHz
Bandwidth	2MHz
Power levels	{-5,-4,-3,-2,-1,0,1,2,3,4,5}
highest power	0 dBm
lowest power	-25dBm
alpha1	0.8
alpha2	0.2
Packet length	200 bytes
Packet interval	100 ms
Data Rate	250 Kbps
Noise figure	5dB
Noise density	-174dBm/Hz

reliability at both dynamic and static body postures, as given n Table 1.

Table 2, presents the simulation parameters adopted for Monte Carlo experimental setup to get the desired results in terms of energy, sustainability and reliability optimization. The proposer test-bed setup is the cornerstone to empower the smart and pervasive healthcare platform. Experimental results reveal the proposed EEA performs better at reasonable PLR unlike the constant TPC method. Therefore, we can claim that the energy dissipation is reduced with acceptable PLR and high sustainability (i.e., battery lifetime) by proposed EEA as compared to the constant TPC with more power drain, less PLR and low sustainability.

X. CONCLUSION AND FUTURE RESEARCH

Elderly patient monitoring through cardiac images to portray the big, clear, and accurate picture of the emergency scenario is very vital for pervasive medical care. This paper contributes in four distinct ways. First, a novel self-adaptive power control based EEA is proposed to reduce energy consumption and enhance the battery lifetime and reliability. Proposed EEA and conventional constant TPC are evaluated by adopting real-time data traces of static (i.e., sitting) and dynamic (i.e. Cycling) activities and cardiac images. Second, a novel joint DL-IoMT framework is proposed for cardiac image-driven remote elderly patients. Third, network performance is optimized by introducing sustainability, energy drain, and PLR and average threshold RSSI indicators. Forth, a Use-case for cardiac image-enabled elderly patient's monitoring is proposed. Proposed EEA is evaluated by considering real-time datasets of cardiac images and two body postures case 1, static i.e., sitting and case2, dynamic i.e., cycling. Besides,

the performance of resource-constrained sensor devices is examined and evaluated by considering the average values of transmission power, and RSSI threshold over both proposed EEA and traditional constant TPC for pervasive and economical medical care. It is revealed through extensive experimental results that proposed EEA enhances energy efficiency, reliability, and sustainability, hence battery lifetime unlike its counter-part i.e., constant TPC. Hence, it can be said that proposed EEA is suitable for candidate for smart, sustainable and reliable healthcare for elderly patients. In near future, we will focus on proposing a cardiac pattern recognition platform in association with the national healthcare and clinical sectors. Besides, developing secure as well as efficient elderly patient monitoring prototypes is also one of future tasks.

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