Priority-Based Time-Slot Allocation in Wireless Body Area Networks During Medical Emergency Situations: An Evolutionary Game-Theoretic Perspective

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***Abstract*—In critical medical emergency situations, wireless body area network (WBAN) equipped health monitoring systems treat data packets with critical information regarding patients' health in the same way as data packets bearing regular healthcare information. This snag results in a higher average waiting time for the local data processing units (LDPUs) transmitting data packets of higher importance. In this paper, we formulate an algorithm for *Priority-based Allocation of Time Slots* (*PATS*) that considers a *fitness* parameter characterizing the criticality of health data that a packet carries, energy consumption rate for a transmitting LDPU, and other crucial LDPU properties. Based on this *fitness* parameter, we design the *constant model hawk–dove game* that ensures prioritizing the LDPUs based on crucial properties. In comparison with the existing works on priority-based wireless transmission, we measure and take into consideration the urgency, seriousness, and criticality associated with an LDPU and, thus, allocate transmission time slots proportionately. We show that the number of transmitting LDPUs in medical emergency situations can be reduced by 25.97%, in comparison with the existing time-division-based techniques.**

***Index Terms*—Hawk–dove game, priority-based allocation of time slots, wireless body area network (WBAN).**

I. Introduction

HEALTHCARE in modern days has been undergoing crucial changes, as the common practice of clinical treatment is gradually being overhauled by ubiquitous healthcare systems [1]. In the past decade, healthcare organizations underwent steep rise of pressure to provide improved healthcare, as the number of chronic disease patients steeply increases every year world wide [2], [3]. Chronic diseases such as heart and lung diseases require real time, continuous, and long-term follow-ups. WBANs [4] can help in ubiquitous and remote health monitoring of patients [5], [6]. Table I lists the important physiological parameters that can be monitored by wireless body area sensors. We also discuss the type of physiological parameter monitored, operation data-rate, and bandwidth for each of these sensors that operate on the IEEE Standard 802.15.6-2012 (IEEE Standard 802.15.6-2012 is a standardization specifically designed to support WBAN-based communications).

TABLE I
Different Types of Wireless Body Area Sensors

Sensor type	Physiological parameter monitored	Data-rate	Bandwidth
ECG	Blood pressure, Heart rate, post-operative monitoring	71-288 kbps	100-1000 Hz
Pulse oximeter	Blood pressure, Heart rate, Blood oxygen saturation (SpO_2)	16 bps	0-1 Hz
Gyroscope insulin actuator	Blood glucose	1600 bps	0-50 Hz
Temperature sensor	Body temperature	120 bps	0-1 Hz
Accelerometer	Post-operative monitoring, fall detection for elderly patients, Parkinsons disease	35 kbps	0-500 Hz

A WBAN comprises of multiple heterogeneous body sensor devices which are capable of monitoring different health attributes, record it in the form of raw health data, and subsequently transmit the data to a local data processing unit (LDPU). The LDPU temporarily stores the health data specific to a patient, and disseminates the same for follow-up analyses. Doctors can remotely monitor patients' physiological condition in real time, and provide crucial medical suggestions in less time. Our paper focuses on WBAN-based remote healthcare and medical services in situations of medical emergencies. We propound an efficient solution of the challenges encountered from a communication perspective while health data are transmitted in a critical medical situation.

A. Motivation

In situations of medical emergencies, multiple LDPUs may transmit healthcare data simultaneously during the same time interval. It is important to discriminate the LDPUs transmitting critical heath data from the ones transmitting data of regular importance. In such cases, frequency division-based transmission in a multisource-single-sink network results in flooding of the sink's receiver buffer. This leads to packet loss and consequent retransmission of the regenerated packets. Moreover, it fails to establish priority among the transmitting LDPUs, based on the criticality of the healthcare information being transmitted. An

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alternate time division-based wireless transmission scheme could, however, prevent the receiver-buffer from being overwhelmed by excessive data arrival-rate. But the major limitation of this uniform time-slot distribution algorithm is that it fails to assign priorities to the transmitting LDPUs based on the importance of the health data that is being transmitted. Also, due to nondiscrimination of data packets, every sender (LDPU) has to wait for a fixed number of time slots before it gets its turn again. However, from a judgemental perspective, the transmitting LDPUs should have a waiting time proportionate to the criticality of their health condition.

B. Contribution

Our paper addresses the aforesaid issues by analyzing priority-based time-slot allocation along LDPUs during critical medical emergency situations from an evolutionary game-theoretic perspective. The primary contributions of this paper are listed below.

1) Critical LDPU-properties such as the importance of health data to be transmitted, energy dissipation factor of an LDPU, and time elapsed since last successful transmission are taken into account to formulate a *fitness* parameter for each LDPU to which the sensor nodes broadcast. Through this formulation, we compute a relative measure of node importance and, thus, prioritize their influence.
2) We design an algorithm for *priority-based allocation of time slots* (*PATS*) based on an evolutionary game, referred to as the *constant model hawk–dove game*, which allows the LDPUs to choose its strategy based on its *fitness*. Adoption of such strategy enables the LDPUs with important health-data gain preference over the regular ones.
3) LDPUs with higher *fitness* are awarded with the highest preference ensuring minimum waiting time between successive transmissions of data packets.

II. Related Works

Karim *et al.* [7] proposed a priority-based preemptive packet scheduling algorithm that outperforms the traditional FCFS and multilevel queue schedulers in terms of transmission delay. A learning-automata-like random early detection (LALRED) of congestion in wired networks is proposed in [8]. The goal of LALRED is to optimize the queue size based on a learning automaton and, thus, detect and avoid congestion early. Michopoulos *et al.* [9] discussed about packet loss, lower throughput, and energy inefficiency in congested wireless sensor networks (WSN). The proposed algorithm automatically adjusts a node's data forwarding strategy with a view of minimal packet drops due to congestion. Congestion control in WSN using ant-based agents is discussed in [10]. In [11], the authors have analyzed the importance of packet drops in WSN through the evaluation of link quality between network nodes. They have used a variant of link state protocol where all nodes gather information regarding the link packet loss from all neighbours. Based on this packet drop information table, each node chooses a cluster head. A fusion of three different techniques spanning across three different layers, viz., hop-by-hop flow control, rate limiting source traffic in the presence of transit traffic, and a prioritized medium access control (MAC) protocol are implemented in [12] to improve WSN efficiency. But in context of WBANs, these protocols are deficient as no internode priority considerations are made. Therefore, no distinction can be drawn between LDPUs transmitting crucial health data from the ones that transmit regular health check-up related data packets. Also, a WBAN consists of heterogeneous sensor nodes—each node has a specific purpose to monitor some specific health parameters. Clearly, in a cluster of such nodes, every node should not be assigned the same priority.

In [13], the authors contributed toward the convergent feature of traffic in WBANs in certain cases which involve packet loss, retransmission, delay in packet delivery, and consumption of extraneous energy arising due to congestion. The authors, however, do not enlighten on the importance of body sensors transmitting critical life-saving health data. A game-theoretic approach to minimize contention delay is proposed in [14]. A modified carrier sense multiple access with collision avoidance (CSMA/CA) protocol is used to allow one sensor at a time to deviate from the standard rules and act like a "cheater." The network performance is analytically derived using a Markov model for worst-case conditions. Misra *et al.* [15] proposed a learning automata-based congestion avoidance scheme (LACAS) that proves to be an efficient automata-based congestion avoidance policy. However, most of these works do not take into consideration the important factor associated with the health data to be transmitted. Our paper, nonetheless, is distinctive due to the specific contributions made for the use of WBANs in medical emergency situations.

III. Communication Architecture

Ubiquitous health monitoring relies on some special characteristics of wireless body sensor nodes. The basic principle of these sensors is that the source of the signals received is the living tissue. In this paper, we discuss the problem scenario only from an on-body sensor perspective. These body sensor nodes are mounted on the patient's body to enable remote monitoring of health parameters. Each such sensor node is deployed to monitor a specific health parameter. For instance, a pulse oximeter measures the oxygen saturation level in blood and the heart rate [16], and an EKG sensor monitors and records the EKG-graph for a patient [17], [18].

The on-body sensor nodes sense health parameters as a continuous function of time, and transmit the same to a portable LDPU via Bluetooth or ZigBee. These LDPUs, in turn, disseminate the data acquired to an anchor node placed inside a medical ward of a hospital. Such a medical ward may have multiple anchor nodes situated distantly to act as a sink to the neighboring LDPUs deployed on patients admitted in that ward. The events sensed and data collected by the body sensors are broadcasted to this sink (LDPU). LDPUs may be designed to communicate with its concerned anchor node through GPRS or Wi-Fi. The anchor nodes are capable of transmitting data packets to remote health-data acquisition center over the Internet for real-time analyses of sensed data. Any deviation from standard

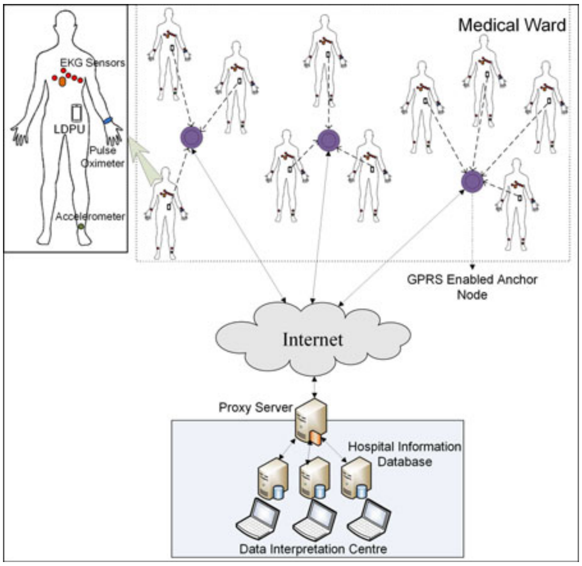

Fig. 1. Communication architecture.

health data is taken into account, and necessary actions, treatments, or even medicines are rushed to the concerned patient as per doctor's recommendation. Fig. 1 provides a pictorial presentation of the WBAN communication architecture.

IV. Formulation of Utility Function

In this section, we focus on designing a *"fitness parameter"* that is used as a measure of LDPU priority. The value of the fitness parameter at time t (Ψ_t) for an LDPU is mathematically calculated based on certain parameters such as 1) the energy dissipation factor, 2) token starvation factor, and most importantly, 3) health-data criticality factor. We discuss the importance of these factors in the formulation of the fitness parameter below.

A. Energy Dissipation Factor

Sensor nodes are, in general, capacitated with limited amount of energy to survive on. Consequently, energy looms large as a constraint for these sensing devices, and, therefore, is crucially important to ensure that the rate of dissipation of energy can be minimized for these sensors. On the other hand, thermal energy harvesting has emanated to be path breaking [19], [20] in the context of body sensor nodes. Few popular sources to harvest energy for body sensors are movement of limbs, locomotion of the human, or even the human body temperature. The prototype development of thermoelectric generator (TEG) chips has certainly acted as a major boost in practical implementation domains involving WBANs. Energy dissipation in an LDPU may result due to multiple reasons, as listed below.

Sensing energy (E_{sn}): As body sensor nodes continuously monitor and record the concerned health parameter of a person over time, there is continuous drainage of energy in sensing. The energy expanded due to sensing in a single time slot by each body sensor node is denoted as E_{sn}.

Transmission Energy (E_{tr}): The transmission energy of a body sensor node E_{tr} is the energy dissipated due to the transmission of a single data packet by that node. The packet may be either originated from the node itself, or it could have reached the node as an intermediate hop toward its destination. E_{tr} usually has a higher magnitude, as broadcasting of health parameters in the form of packets requires considerable amount of energy.

Processing Energy (E_{pr}): In a WBAN, a body sensor node not only acts as a sensing device, but also as a routing device. As a part of intra-WBAN communications, each body sensor receives numerous data packets from multiple other sensors, and route those data packets further, either toward the destination anchor node, or toward another body sensor in its path, after processing the data packet. Processing energy E_{pr} of a body sensor is the energy expended due to processing of a single packet retrieved from the input buffer, and subsequent mapping of the same to its destination through the routing table.

Computational Energy (E_{cm}): The energy consumed to perform preliminary computations on the raw sensed data before it is converted into a packet is termed as the computational energy of that node, and is denoted by E_{cm}. It is noted that the energy consumption due to computations is much less compared to the energy exhausted due to transmission of a data packet.

Definition 1 (Nodal Energy Dissipation Factor): The nodal energy dissipation factor $E_{d_t,i}$ is defined as the maximum energy expended by the ith body sensor node after t time slots is defined as the sum of the energy consumed due to sensing E_{sn}, transmissions E_{tr}, processing E_{pr}, and computations E_{cm} purposes, and the energy exhausted due to channel conditions (such as path fading, path loss, and BER) and, varied signal strength (E_{ch}). $E_{d_t,i}$ and is represented as

$$E_{d_t,i} = E_{sn} \times t + E_{tr} \times N + E_{pr} \times n + E_{cm} \times (N - n) + E_{ch} \tag{1}$$

where n and N refer to the number of packets received and transmitted by a node during t slots.

For nodes capable of harvesting energy, Definition 1 can be modified as

$$E_{d_t,i} = E_{sn} \times t + E_{tr} \times N + E_{pr} \times n + E_{cm} \times (N - n) - E_{hr} \times t + E_{ch}. \tag{2}$$

Definition 2 (Energy Dissipation Factor): We define the energy dissipation factor of an LDPU at time t (ξ_t) as the ratio of the total energy dissipated after t time slots by Z number of component body sensors connected to the LDPU to the sum of each of their initial energy levels. Mathematically,

$$\xi_t = \sum_{i=1}^{Z} E_{d_t,i} \Big/ \sum_{j=1}^{Z} E_{init,j} \quad 0 \le \xi_t \le 1 \tag{3}$$

where $E_{init,j}$ is the energy of the jth body sensor at time $t = 0$ and $E_{d_t,i}$ follows from Definition 1.

B. Token Starvation Factor

In our algorithm, an LDPU may not transmit a data packet without bothering about the transmission status of the other LDPUs. It can only transmit its packets upon reception of a permission *token* from the anchor node it is connected to. Following the acquisition of the token, an LDPU sends data packets within its permissible time slots.

Let τ_t denote the time-stamp corresponding to the last token acquisition by an LDPU, i.e., the time an LDPU has last started transmission of a data packet. Clearly, τ_i can be computed as

$$\tau_i = \tau_c - \tau_t \tag{4}$$

where τ_c indicates the current system time, and τ_t gives an estimate of the time interval during which the LDPU has been idle since its last transmission. Evidently, τ_c has a magnitude greater than or equal to τ_t, indicating $\tau_i \geq 0$. Again, let each time slot, for which the LDPUs contend, be of δ duration ($\delta > 0$).

Definition 3 (Idle Time Slots): Idle time slots of an LDPU ν_t is expressed as the ceiling of the ratio of the time duration elapsed since the LDPU has last transmitted τ_i to the duration of a single slot δ

$$\nu_t = \lceil \tau_i / \delta \rceil. \tag{5}$$

Definition 4 (Limiting Idle Time Slot): Limiting idle time slot $\nu_{\max}$ is the maximum number of time slots that an LDPU may theoretically spend without transmitting. $\nu_{\max}$ is expressed as

$$\nu_{\max} = 2^{M(t)} - 1 \tag{6}$$

where $M(t)$ denotes the number of LDPUs associated with the concerned anchor node. Hence, $\nu_t \in \{0, 1, \ldots, (2^{M(t)} - 1)\}$.

Definition 5 (Token Starvation Factor): Token starvation factor for an LDPU at time t (Υ_t) is defined as the ratio of the number of time slots the LDPU has been idle since its last transmission (ν_t) to the limiting idle time-slot value ($\nu_{\max}$),

$$\Upsilon_t = \nu_t / \nu_{\max} \tag{7}$$

As $\nu_t < \nu_{\max}$, $0 \leq \Upsilon_t \leq 1$.

C. Health Severity Index

The third and the most important factor taken into consideration is the health severity of the patients. In this paper, we put forward a generalized metric for the measurement of average importance of the healthcare data that are to be transmitted by the LDPU at a given time instant.

Let, for person of a given age and gender, the *reference range* of a particular health parameter that is being monitored, be within Θ_{lc} and Θ_{uc}, under normal health conditions. Θ_{lc} and Θ_{uc} denote the upper and lower limits of the *reference range*, respectively. At a given time t, the recorded value of that particular health parameter is denoted by Θ_t. A brief description of the standard procedure for obtaining Θ_{lc} and Θ_{uc} is described in Appendix A.

Definition 6 (Health Severity Index): The health severity index of a patient at time t is denoted by ρ_t. It is mathematically expressed as

$$\rho_t = \left| \frac{(\Theta_{uc} - \Theta_t)^2 - (\Theta_t - \Theta_{lc})^2}{(|\Theta_{uc}| + |\Theta_{lc}|)^2} \right|. \tag{8}$$

Clearly, $\rho_t = 0$ when $\Theta_t = (\Theta_{lc} + \Theta_{uc})/2$. Theoretically, in some cases, the value of rho_t may exceed 1 (which is hardly the case in practical scenarios). In such cases, ρ_t is approximated to 1 for computational benefit. Therefore, in practice, $0 \leq \rho_t \leq 1$.

Finally, after properly defining the factors that influence the *fitness parameter* Ψ_t, we define it in Definition 7.

Definition 7 (Fitness Parameter): The fitness parameter Ψ_t of a patient at time t is defined as the weighted average of the energy dissipation factor ξ_t, token starvation factor Υ_t, and health severity index ρ_t of that patient. Ψ_t is mathematically expressed as

$$\Psi_t = \frac{\lambda_1 \xi_t + \lambda_2 \Upsilon_t + \lambda_3 \rho_t}{\lambda_1 + \lambda_2 + \lambda_3} \tag{9}$$

where λ_1, λ_2, and λ_3 are constant values specific to the health parameters to be measured. Also, they depend on the patient's age, sex, and past medical history. The value of Ψ_t ranges between $0 \leq \Psi_t \leq 1$. A high value of Ψ_t indicates that an LDPU is willing to transmit highly critical health data of the concerned patient, and vice versa.

V. PATS: Priority-Based Allocation of Time Slots

In this section, we propose an algorithm for priority-based allocation of time slots (PATS) using an extension of the evolutionary game theory [21]. The primary advantage of game theory is that it provides insight into situations that arise due to conflict of interests and individual profit maximization strategies. It develops a mathematical framework to analyze decision making where interdependence of the players is considered. Evolutionary game theory is a branch of classical game theory [22] which involves repeated interactions within the population. Each entity in the population adopts a game-playing strategy, and acts in accordance with a particular strategy. The pay-offs corresponding to the strategy depend on the strategies adopted by the coplayers as well. Unlike similar existing algorithms, in evolutionary game theory, an individual's move during a game is not out of deliberation; rather, it is an act driven by learning. The process is similar to natural selection to determine how the population evolves. In comparison with similar other approaches, such as greedy algorithms, evolutionary game theory-based solution approach not only adds dynamicity to the algorithm, but also, allows the LDPUs to strategize. In this paper, we design an n-player, noncooperative evolutionary game algorithm, termed as, the *constant model hawk–dove game*, which can be treated as a variant of the traditional *hawk–dove game*.

In the game proposed in this paper, the anchor nodes stand as the game coordinator with the LDPUs connected to it as the participating players of the game. A new game is played after every T interval of time. Mathematically,

$$T = \epsilon + k\delta \tag{10}$$

where k is the total number of time slots to be distributed among the LDPUs, each of duration δ, and ϵ is the overhead time spent by the anchor node for game computation, evaluation, and analyses.

In our game model, a player (an LDPU) can take either an aggressive strategy (*hawk*) or a timid one (*dove*), based on the *fitness* parameter Ψ_t. The resource that the LDPUs play for is the time slot(s) that allow(s) an LDPU to transmit its data packets over the acquired time slots. As we have shown before, $0 \leq \Psi_t \leq 1$. An LDPU chooses the hawk or dove policy ($S = \{H, D\}$) according to the following strategy:

$$S = \begin{cases} D & \text{if } 0 \leq \Psi_t < \phi_1 \\ D & \text{if } \phi_1 \leq \Psi_t < \phi_2 \text{ with probability } (1-p) \\ H & \text{if } \phi_1 \leq \Psi_t < \phi_2 \text{ with probability } p \\ H & \text{if } \phi_2 \leq \Psi_t \leq 1 \end{cases} \quad (11)$$

where ϕ_1 and ϕ_2 are LDPU specific, experimental constants, typically ranging of $0 < \phi_1, \phi_2 < 1$ and $\phi_1 < \phi_2$. ϕ_1 indicates the value of Ψ_t, below which an LDPU is bound to adopt the *dove* strategy. If Ψ_t has a value above ϕ_2, the LDPU adopts the *hawk* policy. An intermediate value of Ψ_t lets an LDPU choose the *hawk* strategy with p probability, and the *dove* strategy with complementary probability, based on its learning. The value of p ($0 \leq p \leq 1$) is determined by a player as a part of its learning policy. Each LDPU chooses a policy whenever it opts to send some data packets, and sends its choice (H or D) to the connected anchor node. The anchor node receives multiple such requests for the contention of time slots. It, then, sends back tokens in a prioritized fashion among the LDPUs. For a set of LDPUs $L = \{L_1, L_2, \ldots, L_{m_t}\}$ connected to an anchor node,

$$\sum_{L_i \in A, A \subseteq L} k_1 \times L_i + \sum_{L_j \in B, B \subseteq L} 1 \times L_j = k, A \cap B = \emptyset, |A| + |B| = m_t \quad (12)$$

where $|A|$ and $|B|$ are the number of players adopting H or D strategies, respectively. k_1 is the number of slots allocated to each hawk. The total number of LDPUs willing to transmit at time t is given by m_t. Clearly, $m_t \leq M(t)$. We introduce a function $f(\cdot,\cdot)$ to compute the time slots to be distributed among the dove-strategic LDPUs. $f(\cdot,\cdot)$ considers the number of hawks h and doves d as inputs, such that $h + d = m_t$ and is expressed as

$$f(h, d) = \begin{cases} 1 & \text{if } d < k\%h \\ b, b \in \{0, 1\} & \text{otherwise} \end{cases} \quad (13)$$

where $k\%h$ are the slots remaining to be distributed among the doves. f assigns every dove a unit time slot if possible, otherwise it assigns unit time slot to few randomly chosen doves. We design and analyze the pay-off matrix corresponding to the *constant model hawk–dove game* as shown in Table I. It is designed for a specific scenario, where a total of ($m_t = x + y + 1$) LDPUs wish to transmit data at time t. For an h-hawk-d-dove system, hawks are each awarded with $\lfloor \frac{k}{h} \rfloor$ unit time slots, and the doves are awarded time slots as per $f(\cdot,\cdot)$. Algorithm 1 elaborates the time-slot allocation by the LDPU.

Using PATS, we achieve two objectives. First, we distinguish the LDPUs possessing critical health data and willing to transmit from the ones transmitting regular health check-up related data. This helps us to increase the precedence of nodes transmitting important data packets, and, to ensure that critical healthcare data packets are transmitted before the regular ones. Thus, we minimize the transmission delay for these critical packets. Second, we ensure that other nodes are restricted to transmit when a node with critical health data does so. This diminishes the chance of packet collision in the network, and also the chance of the LDPU input-buffer overflow. We now discuss some of the results obtained through PATS in WBAN.

Algorithm 1 Priority-Based Allocation of Time-Slots (PATS)

Input: Strategy vector comprising of individual strategies of m LDPUs, denoted by $S_L = \{S_{L_1}, S_{L_2}, ..., S_{L_{m_t}}\}$, such that $S_{L_i} \in \{H, D\}$.
Output: Allocation of time-slots based on the game outputs.

1: $hawk\_count = 0$; $dove\_count = 0$;
2: **for** each L_i **do**
3:   **if** $S_{L_i} = H$ **then**
4:     $hawk\_count$++ ;
5:   **else**
6:     $dove\_count$++;
7:   **end if**
8: **end for**
9: $hawk\_slots \leftarrow hawk\_count \times \lfloor \frac{k}{hawk\_count} \rfloor$ /* Total slots to be allocated to hawks */
10: $dove\_slots \leftarrow k - hawk\_slots$ /* Total slots to be allocated to doves */
11: **for** each L_i **do**
12:   **if** $S_{L_i} = H$ **then**
13:     Allocate $\lfloor \frac{k}{hawk\_count} \rfloor$ unit time slots;
14:   **else**
15:     **if** $S_{L_i} = D$ and $dove\_slots \neq 0$ **then**
16:       Allocate unit time slot ;
17:       $dove\_slots$ −−;
18:     **else**
19:       Transmit NAK;
20:     **end if**
21:   **end if**
22: **end for**

Proposition 1: The running time complexity of PATS is $O(m_t)$, where m_t is the number of LDPUs that has a frame to transmit at time t.

Proof: We obtain the recurrence relation for PATS from Algorithm 1 as

$$T(m_t) = T(m_t - 1) + c, \, T(1) = c' \quad (14)$$

where $T(m_t)$ is the time taken to execute PATS for m_t number of LDPUs. The running time complexity for executing lines 12 through 21 of Algorithm 1 is $c = \Theta(1)$. We obtain the recurrence relation for the computational time complexity of PATS as

$$T(m_t) = T(m_t - k) + kc. \quad (15)$$

Finally, we get,

$$T(m_t) = T(1) + (m_1 - 1)c$$
$$\Rightarrow T(m_t) = O(m_1 - 1) \simeq O(m_t). \quad (16)$$

This completes the proof. ■

TABLE II
PAY-OFF MATRIX FOR *CONSTANT MODEL HAWK–DOVE GAME*

	(x+y) Hawks	x Hawks + y Doves	(x+y) Doves
Hawk	$\lfloor \frac{k}{x+y+1} \rfloor$	$\lfloor \frac{k}{x+1} \rfloor$	$k.$
Dove	$f(x+y,1)$	$f(x,y+1)$	$f(0,x+y+1).$

Corollary 1: For an h-hawk-d-dove system, the tightest lower bound of the LDPUs allowed to transmit within T interval is $O(h)$.

Proof: For a total of k time slots available during a single iteration, the hawks are allocated time slots as per Table II, prior to the doves. The total number of slots h_{tot} allocated to the hawks is given by

$$h_{tot} = h \times \lfloor k/h \rfloor. \tag{17}$$

Now, in order to obtain the tightest lower bound of the number of LDPUs allowed to transmit, minimum number of doves should be allowed to transmit during the same iteration. Thus, we have

$$\begin{aligned} k &= h_{tot} = h \times \lfloor k/h \rfloor \\ &\Rightarrow k - (h \times \lfloor k/h \rfloor) = 0 \\ &\Rightarrow k = ch, c = 1, 2, \ldots, \text{upto } \infty \\ &\Rightarrow k\%h = 0. \end{aligned}$$

This implies that no time slots are allocated for doves. Only the hawks are allowed to transmit. Thus, the tightest upper bound for the number of LDPUs transmitting within T interval is equal to $O(h)$.This completes the proof. ■

Proposition 2: Unlike the existing time-based or frequency-based transmissions of m_t LDPUs within time T, PATS reduces the number of transmitting LDPUs by $m_t - h - \min(d, k\%h)$.

Proof: We assume that m_t is the total number of transmitting LDPUs present in the system at time t.

For an h-hawk-d-dove system (where, $h + d = m_t$), the total number of time slots allocated to h hawks is given by $h\lfloor \frac{k}{h} \rfloor$. Therefore, the number of remaining slots for that iteration is $k - h\lfloor \frac{k}{h} \rfloor = k\%h$.

This implies that the total number of doves that are allowed to transmit is expressed as $\min(d, k\%h)$. Therefore, the total number of LDPUs that are awarded with time slots during an iteration w is expressed as

$$w = h + \min(d, k\%h). \tag{18}$$

Clearly, $m_t \geq w$. Consequently, the number of LDPUs that are debarred from transmission during that cycle is

$$m_t - w = m_t - h - \min(d, k\%h). \tag{19}$$

On the contrary, in existing time-based or frequency-based data transmission techniques, all the requesting LDPUs are allowed to transmit during every cycle. Therefore, in such cases, the number of transmitting LDPUs remain m_t. This completes the proof. ■

VI. SIMULATION RESULTS

In this section, we evaluate the performance of the proposed algorithm, PATS, using MATLAB. We study the variation of Ψ_t with the variation of each contributing factor, and measure and compare the results in each such case. We also project some performance comparison of PATS with standard TDMA and FDMA transmission protocols.

A. Effect of the Contributing Factors on the Fitness Parameter

Experimental Settings: The experimental WBAN system consists of 30 LDPUs. We first show the impact while plotting the LDPU-fitness Ψ_t against a parameter, the other two parameters are kept constant (in our case, 0.5). Also, the values of λ_1, λ_2, and λ_3 are taken as 3, 2, and 5, respectively, to ensure ordered preference among the three factors.

Fig. 2(a) shows the plot of the energy dissipation factor ξ_t against Ψ_t. Analyzing the graph, we observe that, with a wide range of variation in the value of ξ_t, Ψ_t varies mostly between 0.35 and 0.65, denoting a variation of around 0.15 in either side of its mean value (0.5). Fig. 2(b) depicts the fluctuation of the value of Ψ_t with the change in the token starving factor Υ_t. We observe that the variation of the values of Ψ_t lies within 0.1 units of the mean value, in each side of it, symbolizing a comparative low impact of Υ_t on Ψ_t. In Fig. 2(c), the plot of health severity index ρ_t against Ψ_t is shown. Unlike the previous two cases, we observe that the values of Ψ_t are generally spread widely between 0.25 and 0.75, in either side of the mean (0.5). A higher variance indicates a higher influence of ρ_t on Ψ_t, compared to the other two factors.

After analyzing the above three graphs thoroughly, we attain a clearer perspective regarding the influence of certain factors on Ψ_t, and also an impression on the assignments of the weights (λ_1, λ_2, and λ_3) corresponding to each of the factors.

B. Performance Analysis

Experimental Settings: The experiments performed for performance analyses involve wireless communication over a single AWGN channel for 20 LDPUs over 20 time slots. The data modulation scheme used is BPSK and the buffer size at the receiver end are assumed to be constant throughout the experiments.

Fig. 3(a) demonstrates the comparison of the number of LDPUs allowed to transmit to the total number of such LDPUs present in the system. Unlike the standard TDMA solutions, PATS considers the fitness of the LDPUs while allocating time slots, thereby prioritizing the critical data transmitting LDPUs by rewarding with higher number of time slots. PATS also outperforms traditional FDMA and advanced orthogonal FDMA (OFDMA) [23] solutions with respect to the number of packet drops, as shown in Fig. 3(b). Since the number of transmitting LDPUs is considerably reduced, eventually only the critical data packets manage to the receiver end successfully, thereby, improving the packet drop rate remarkably. As a

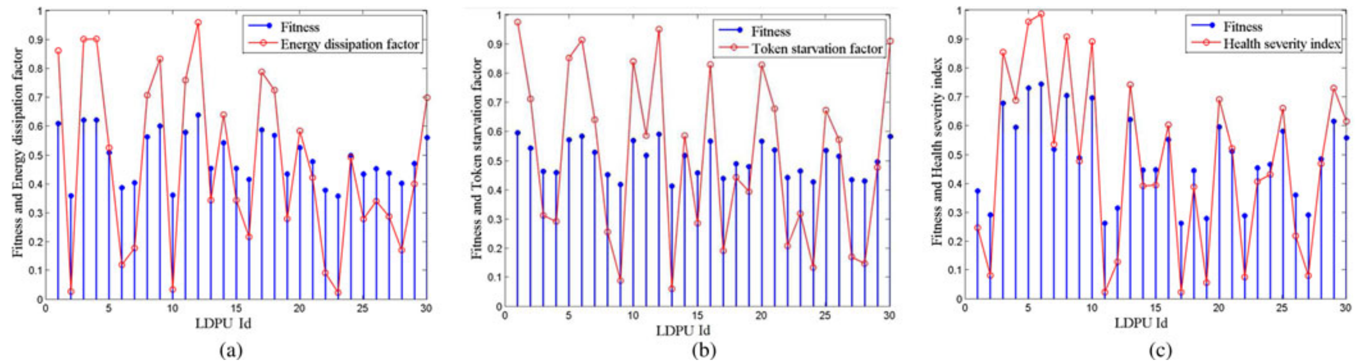

Fig. 2. Effect of contributing factors on fitness parameter. (a) Fitness versus energy dissipation factor graph. (b) Fitness versus token starvation factor graph. (c) Fitness versus health severity index graph.

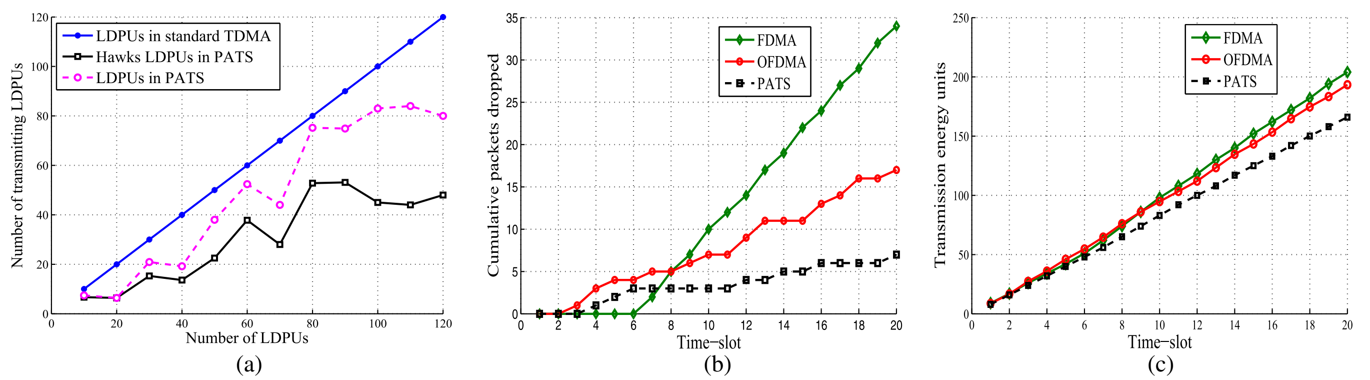

Fig. 3. Performance analysis of PATS. (a) Comparison of number of transmitting LDPUs. (b) Comparison of packet drops. (c) Comparison of transmission energy dissipation.

consequence of the packet drop rate, the total energy exhausted due to transmission and successive retransmission(s) is also reduced, as reflected in Fig. 3(c).

VII. Conclusion

This paper considers an evolutionary game model that allows an LDPU to adopt an active or a passive strategy while transmitting sensed data, and compete in the game. A fair game strategy based on LDPU-fitness helps LDPUs that run low on energy, or transmit crucial data, or has been idle for a longer period, through gaining higher priority. We conclude that controlled transmission by the LDPUs not only diminishes the average number of packets transmitted over the WBAN during a time interval, but also ensures distinctive reduction in the packet-drop rate and the energy dissipation. Most importantly, PATS rewards critical LDPUs with higher number of time slots, and, thus, eventually prioritizing patients with high severity in health conditions.

Finally, our future works include investigating variable buffering delays and variable queue capacities. Also, we have an aim to implement PATS in a prototype model of medical disasters. Implementation of LDPU-specific health data importance factor is also a challenge as each LDPU collects health data from the heterogeneous body sensors. An intelligent measure of variance of measured health data from a standard dataset is always a challenge.

Appendix A
Reference Range Calculation

The upper and lower limiting values of the range is often estimated by the *t-distribution*. For a normal sample size of n ($n > 0$), first the mean($\bar{x}$) is computed as

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}, \quad \forall x = 1(1)n.$$

Then, the standard deviation of the sample s_x is computed as

$$s_x = +\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2}.$$

However, as the population mean μ and the population standard deviation σ_x both are unknown for most practical cases, we predict the limiting values of the reference range using the *t-distribution*. The $(1-\alpha)100\%$ confidence interval (CI) [also referred to as the prediction interval (PI)] is then computed for $(n-1)$ degrees of freedom. The equations for estimating the values of Θ_{lc} and Θ_{uc} are given below

$$\Theta_{lc} = \bar{x} - \sqrt{\frac{n+1}{n}} \times s_x \times t_{\alpha,n-1}$$

$$\Theta_{uc} = \bar{x} + \sqrt{\frac{n+1}{n}} \times s_x \times t_{\alpha,n-1}.$$

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