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 to the traditional time-division based techniques.**

***Index Terms*—Wireless Body Area Network, Hawk-Dove Game, Priority-Based Allocation of Time-Slots.**

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]. 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 work 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 situations of medical emergencies, a frequency division-based wireless transmission in a multi-source-single-sink communication topology flood the sink's receiver-buffer, which leads to packet loss and consequent retransmission of the packets. Moreover, it fails to establish priority among the transmitting LDPUs, based on the criticality of the healthcare information being transmitted. An 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 non-discrimination of data packets, every sender (LDPU) has to wait for a fixed number of time-slots before it gets it 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 work addresses the aforesaid issues by analyzing priority-based time-slot allocation along LDPUs during critical medical emergency situations from a evolutionary game theory perspective. The primary contributions of this work are listed below.

- 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.
- 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.
- 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. [6] proposed a priority-based preemptive packet scheduling algorithm that outperforms the traditional FCFS and multi-level queue schedulers in terms of transmission delay. A learning-automata-like random early detection (LALRED) of congestion in wired networks is proposed in [7]. 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. [8] 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 [9]. In [10], 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 [11] to improve WSN efficiency. But in context of WBANs, these protocols are deficient as no inter-node 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 [12], the authors contributed towards 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 [13]. 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. [14] proposed on 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 importance-factor associated with the health-data to be transmitted. Our work, nonetheless, in 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, and an EKG sensor monitors and records the EKG-graph for a patient [15], [16].

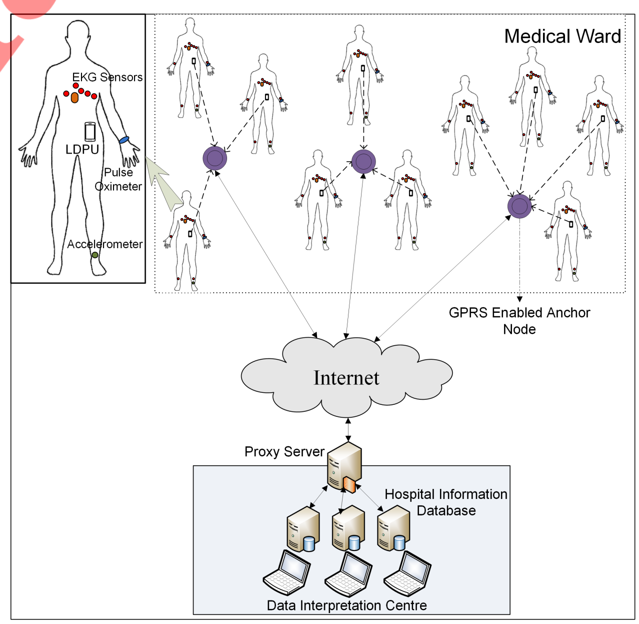

Fig. 1: Communication Architecture

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 broadcast 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 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 (a) the energy dissipation factor, (b) token starvation factor, and most importantly, (c) 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 (TEH) has emanated to be path breaking [17], [18] 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 thermo-electric 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 expended 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 towards 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 towards the destination anchor node, or towards 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 : The nodal energy dissipation ($E_{d_t,i}$) is defined as the total energy expended by the i^{th} 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 is represented as:

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

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:

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

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,

$$\xi_t = \sum_{i=1}^{Z} E_{d_t,i} / \sum_{j=1}^{Z} E_{init,j} \quad 0 \leq \xi_t \leq 1 \quad (3)$$

where $E_{init,j}$ is the energy of the j^{th} 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 the LDPU has last started transmitting a data-packet. τ_c indicates the current system time, and τ_i gives an estimate of the time interval during which the LDPU has been idle since its last transmission. Clearly, τ_i can be computed as:

$$\tau_i = \tau_c - \tau_t \quad (4)$$

Evidently, τ_c has a value 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 (ν_{max}) is the maximum number of time-slots that an LDPU may theoretically spend without transmitting. ν_{max} is expressed as,

$$\nu_{max} = 2^Z - 1 \tag{6}$$

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

Definition 5. Token Starvation Factor: Token starvation factor (ν_t) 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 to the limiting idle time-slot value (ν_{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 measurement of the average importance of the healthcare data that is to be transmitted by the LDPU at a given time instant.

Let, for person of a given age and sex, 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.

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:

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

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 [19]. Evolutionary game theory is an branch of classical game theory [20] 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 co-players as well. Unlike other simpler traditional 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. In this paper, we design an n-player, non-cooperative evolutionary game algorithm, termed as, the *constant model hawk-dove game*, which can be treated as a variant of the the traditional *hawk-dove game*.

In the game proposed in this work, 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:

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

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 contention of time-slots. It, then, sends back tokens in a prioritized fashion among the LDPUs. For a set of LDPUs $L = \{L_1, L_2, ..., L_m\}$ connected to an anchor node,

$$\sum_{L_i \in A, A \subseteq L} k_1 \times L_i + \sum_{L_j \in B, B \subseteq L} 1 \times L_j = k, A \cap B = \emptyset, |A| + |B| = m \tag{11}$$

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. 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 $h + d = m$ and is expressed as,

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

$k\%h$ 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. to 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 $(m = x + y + 1)$ 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.

TABLE I: 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	$f(x+y,1)$	$f(x,y+1)$	$f(0,x+y+1).$

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. Secondly, 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.

Proposition 1. *The running time complexity of PATS is $O(m_t)$, when m LDPUs are present in the system at time t.*

Proof: From Algorithm 1, we obtain the recurrence relation of PATS as,

$$T(m_t) = T(m_t - 1) + c, \; T(1) = c \tag{12}$$

where, T_m is the time taken to execute PATS for m_t LDPUs. $c = O(1)$ is the running time complexity for executing line 12

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**

to 21 of Algorithm 1. Applying it by the method of recurrence relation we get that,

$$T(m_t) = T(m_t - k) + kc$$

Finally, we get,

$$T(m_t) = T(1) + (m_1 - 1)c \tag{13}$$

$$\Rightarrow T(m_t) = O(m_1 - 1) \simeq O(m_t) \tag{14}$$

This completes the proof. ∎

Proposition 2. *The total number of LDPUs allowed to transmit within T interval is $h + min(d, k\%h)$.*

Proof: For an h-hawk-d-dove system, total number of time-slots allocated to h hawks are $h\lfloor \frac{k}{h} \rfloor$. Remaining slots are, $k - h\lfloor \frac{k}{h} \rfloor = k\%h$. Thus, total number of doves allowed to transmit are $min(d, k\%h)$. Thus, total number of LDPUs that are awarded with time-slots are $h + min(d, k\%h)$. This completes the proof. ∎

Proposition 3. *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, hawks are allocated time-slots as per Table I. So the total number of slots (h_{tot}) allocated to the hawks are,

$$h_{tot} = h \times \lfloor k/h \rfloor \tag{15}$$

In order to obtain the tightest lower bound, minimum number of doves should be allocated. Thus, we should have,

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

Thus, no time slots are allocated for doves. Only the hawks are allowed to transmit. Thus, the tightest upper-bound is equal to $O(h)$. This completes the proof. ■

Corollary V.1. *Unlike traditional time-based or frequency-based transmission of m LDPUs within time T, PATS reduces the number of transmitters by $m - h - min(d, k\%h)$.*

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_t, λ_2, and λ_3 are taken as 3, 2, and 5, respectively, to ensure ordered preference amongst 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 involves 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 is 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 solutions with respect to the number of packet drops, as shown in Fig. 3(b). Since the number of transmitting LDPUs is considerable reduced, eventually only the critical data packets manage to the receiver end successfully, thereby, improving the packet drop rate remarkably. As a 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 work 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, future work 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 data-set is always a challenge.

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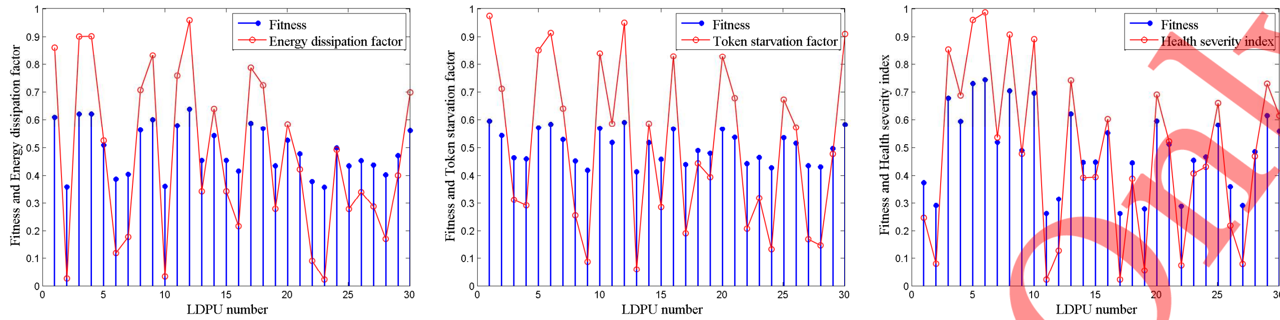
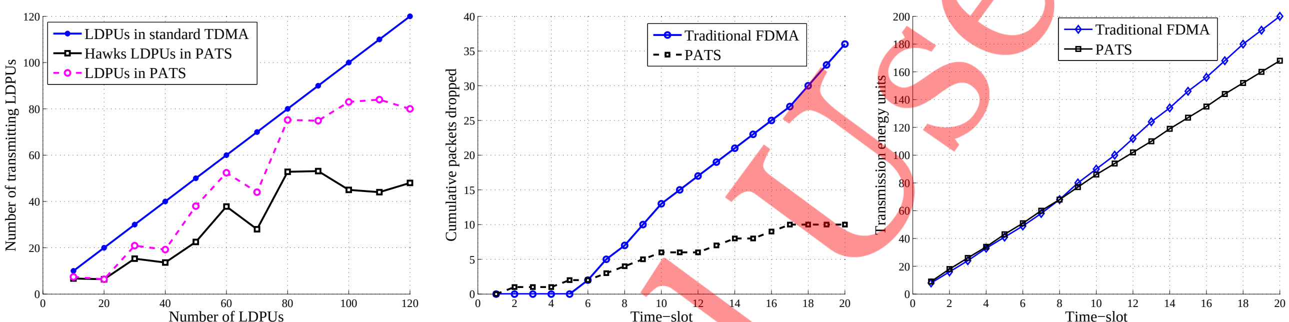


(a) Fitness vs. energy dissipation factor graph (b) Fitness vs. token starvation factor graph (c) Fitness vs. health severity index graph

Fig. 2: Effect of contributing factors on fitness parameter



(a) Comparison of transmitting LDPU number (b) Comparison of packet-drops (c) Comparison of transmission energy dissipation

Fig. 3: Performance analysis of PATS

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