# A Cooperative Bargaining Solution for Priority-Based Data-Rate Tuning in a Wireless Body Area Network

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***Abstract*—In this paper, we propose a cooperative game theoretic approach for data-rate tuning among sensors in a Wireless Body Area Network (WBAN). In a WBAN, the body sensor nodes implanted on a human body typically communicate through a capacity-constrained single channel. This is a serious concern because most applications in WBANs involve real-time data streaming and providing useful notifications and efficient feedback to the patients or other users according to their health conditions. To increase the Quality of Service (QoS), we need an efficient data-rate tuning mechanism, which tunes the data-rate of a sensor based on the criticality of health parameter measured through it. Our approach considers the unique features typical of WBAN applications, and provides a generalized solution for the problem. We propose a cooperative game theoretic approach, based on the Nash Bargaining Solution (NBS), which does not only provide priority-based tuning, but also maintains the fairness axioms of game theory. The proposed approach yields 10% average increase in data-rates for the sensor nodes that have critical physiological data to transmit. We also validate the approach through real system implementation with the help of real sensor devices such as heart rate sensor, and pulse oximeter.**

***Index Terms*—Wireless Body Area Network (WBAN), bargaining power, generalised nash bargaining solution (NBS), cooperative game, data-rate tuning.**

## I. Introduction

In this paper, we identify and address an important research concern—tuning of data-rate of the body sensor nodes based on priority of sensed physiological data. These nodes transfer patients' physiological data to some monitoring unit. Also, in mission critical applications, such as real-time health monitoring of soldiers in battlefield, and emergency health monitoring in a disaster scenario, it may be required to reduce the rate of packet failures and transfer delays as body sensor nodes are generally used in real-life applications [1]. Therefore, tuning the data-rate of the sensors is fundamentally prudent.

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Proportional tuning, which only focuses on the minimum requirements of the sensors, is not sufficient to provide an optimal solution as it does not include health specific and network specific parameters into consideration. Thus, in this paper, we present the concept of utility function and propose a solution using Nash Bargaining Solution (NBS), an approach which is based on co-operative game theory.

The contributions of the proposed work are as follows:

- We derive a generalized index, for measuring the criticality of sensed health data of all body sensors.
- We contemplate the involvement of health, network and sensor characteristics using different parameters, while designing the utility function for the sensors.
- We employ real sensors such as heart rate sensor, and pulse oximeter to validate the proposed work.

## II. Related Works

While there is deficiency of work on data-rate tuning in WBANs, there exists some relevant ones, which are mentioned here. Misra and Sarkar [2] proposed a priority-based time slot allocation algorithm based on constant model hawk-dove game, to address successful data transmission in critical medical emergency situations. These apart, Walsh and Hayes [3] addressed the throughput rate problem using low-order and static anti-windup control laws to improve the overall performance of an IEEE 802.15.4 wireless sensor network. Zhen *et al.* [4] studied the procedure of learning the sensitivity of neurometric application fidelity to electroencephalography (EEG) data and use this sensitivity to develop algorithms that minimizes energy usage in EEG sampling and optimizes the utilization of limited data buffer. However, this work does not consider other WBAN sensors. Xin *et al.* [5] proposed a Genetic Programming-based system—*AdaSense*, which optimizes sample rates for single and multi-activity classification. However, these works do not consider the criticality of physiological parameters and energy constraints while determining the data rate of a sensor at certain time.

The approach of resource bargaining was also explored in the past for solving problems in different network domains. For instance, Liang *et al.* [6] developed dynamic resource allocation schemes with incomplete information, based on online test-optimization strategy. Mazumder *et al.* [7] used the concept of bargaining in the context of packet-switched networks. Some studies of Pareto optimality and local optimization procedures are presented in this paper. Kelly [8] and Kelly *et al.* [9] studied the authors considered the problem of charging and rate-allocation based on valuation of utility function. It is shown that socially optimizing solutions can be obtained for achieving user optimization. Jiang and Howitt [10] proposed a multi-domain load balancing scheme to adaptively balance resource utilization and co-channel interference.

*Synthesis*: It is noteworthy that these approaches are not suitable for WBANs because body sensors have specific requirements and specifications, which differ from those of terrestrial sensor and other wireless networks. Despite the fact that some past works using game theoretic approaches are present, WBAN specific framework design is necessary for patient monitoring or post-operative care in hospitals.

The proposed cooperative game theoretic approach considers WBAN-specific problems while addressing fairness and Pareto optimality in the context of data-rate tuning. Indeed, the implementation of game theoretic approach incurs slightly additional overhead in respect of energy consumption. However, the longer run benefits outweigh the marginally increased energy consumption, as such approaches significantly reduce the packet re-transmission rate of the network.

## III. WBAN Architecture

We consider a WBAN consists of various heterogeneous sensors that are attached on a patient's clothes or on the body (non-invasive) such as ECG sensors, pulse oximeters, thermistors, and SpO2. These sensors are capable of continuously measuring the heart rate, blood pressure, body temperature and oxygen saturation in blood ubiquitously, while providing the patients the opportunity and freedom of being mobile. Apart from sensing, these body sensor nodes must also convert the sensed analog signals into digital information before effective transmission of the same. They should also meet other criteria such as energy and computational efficiency.

Furthermore, PPU is a device that receives all the information sensed and transmitted by the body sensors and informs the users or monitoring persons (e.g., nurses and doctors) via an external gateway or a display in the devices (in case of informing the patient himself/herself). Both the Star and the Star-Mesh hybrid topologies are very useful in WBANs [11].

Another challenge in body area networking is the heterogeneity of sensors. Different sensors exhibit differences in transmitted data rates [12]. Due to heterogeneity there exists significant difference in data rates of various sensors that communicate through a shared channel of limited capacity. Therefore, proper optimization of data-rates is necessary to improve the overall network performance. However, any proportional tuning mechanism, which is based on tuning data-rate of sensors only computed from the proportion of minimum demands, is not sufficient. It is also important to consider other criteria such as severity of sensed physiological data, packet transmission failures, and energy expenditures while optimizing the data-rate of a particular sensor. We propose some definitions for each sensor to estimate these parameters.

*Definition 1. (Criticality Index):* The Criticality Index (CI) for a particular sensor is the ratio of deviation in sensed physiological data and the normal value of that physiological parameter. Mathematically, CI of the $i^{th}$ sensor is,

$$CI_i = \frac{|\xi_s - \xi|}{\xi}. \tag{1}$$

where, $\xi_s$ is the sensed measurement through the $i^{th}$ sensor, and $\xi$ is the normal value for the corresponding physiological parameter.

$(\xi_s - \xi)$ indicates the difference between the sensed value and the normal value of a particular physiological parameter. We take the absolute difference to represent the percentage of fluctuation over the normal value.

*Definition 2. (Failure Probability):* The Failure Probability of the $i^{th}$ sensor at time instant $t(P_{i,t})$ is the probability of unsuccessful packet transfers, within the time instant $(t-\Delta)$ and $(t+\Delta)$, where $\Delta$ is a pre-defined short time span.

Srinivasan *et al.* [13] derived a metric $\beta$-factor to measure wireless link burstiness. Their work witnessed that in a network with high $\beta$-factor the chance of an immediate transmission success after a failed packet transmission is very low. Therefore, we envision to penalize a body-sensor with high packet transmission failure probability by reducing its utility, which is described in detail in the next section.

It is not possible in practical to predict the failure probability as 0 or 1, as there does not exist any algorithm that can foresee 0% or 100% collision chance or other network errors. Thus, we avoid the marginal values of Failure Probability and consider $1 > P_{i,t} > 0$. The main contributing factor behind failed packet transmissions is packet collision. Other causes such as wireless multi-path fading, channel error, distortion, attenuation and interference from nearby signals may cause packet error. However, in this work we assume these other effects as negligible and equal for all the body sensors at a certain time instant.

*Definiton 3. (Power Consumption Ratio):* The Power Consumption Ratio of the $i^{th}$ sensor at time instant $t$ is the ratio of power consumption by the $i^{th}$ sensor to its initial power, within the time instant $(t-\Delta)$ and $(t+\Delta)$, where $\Delta$ is a pre-defined short time span.

In this paper we propose a priority-based dynamic tuning mechanism. To do so, we incorporate a cooperative game theoretic approach based on the Nash Bargaining Solution (NBS) [14]–[16].

## IV. Mathematical Framework

We formulate the problem of priority-based dynamic data-rate tuning in WBAN as a cooperative game, in which groups of players (i.e., the body sensor nodes) enforce cooperative behavior, by choosing their strategies for data-rate tuning as a consensus decision making process, which leads to an optimal result for all individuals. The nodes always try to reach an agreement that gives mutual advantage. Through bargaining, the nodes attempt to jointly agree on the sharing of resources (channel capacity), to optimize their performance, and, in turn, increase the efficiency of the whole network. Each node is self-interested, and aims at obtaining the highest data-rate for its own use. This scenario is equivalent to a *bargaining problem*.

Though the the goal of the sensors is to sense physiological stimulation and transmit the sensed information, we envision the situation as an abstraction of their desires within the PPU. This abstraction assumes that the sensors do not want to be treated equally as normally they do not possess same health, network and energy factors.

We assume that total $m$ number of sensors are participating in the resource bargaining process. They place their respective demands to PPU. The PPU, finally, optimizes the data-rate for each of them. Based on certain parameters, we derive the utility function of each sensor. The utility function of the $i^{th}$ sensor at time $t$ is denoted by $U_i(S_{i,t})$, where $i = 1,2,\ldots,$m. Therefore, we get a closed set to represent all possible utilities of participating sensors. Let it is denoted by $S$. The set $S$ is known as the *joint utility set* or a *feasible utility set* [17].

$$S = \{U_1(S_1), U_2(S_2), \ldots, U_m(S_m)\} \in \mathbb{R}^n. \tag{2}$$

Each sensor node has a minimum demand of data-rate for which it competes. Below this lower limit, the nodes do not cooperate in the game. This point is termed as the *disagreement point*. The disagreement point for the $i^{th}$ sensor is denoted by $S^i_{min}$, where $i = 1,2,\ldots,$m. Furthermore, the set of disagreement points for each player is defined as:

$$S_{min} = \left\{S^1_{min}, S^2_{min}, \ldots, S^m_{min}\right\} \in \mathbb{R}^n. \tag{3}$$

*Definition 4. (Utility of Sensor):* The Utility for the $i^{th}$ sensor at current time instant $(t+1)$ is defined as:

$$U_i(S_{i,t+1}) = \frac{CI_{i,t}\left[S_{i,t+1} - S^i_{min,t+1}\right]}{\frac{\tau_{i,t}}{E_i} + P_{i,t}}. \tag{4}$$

subject to, $S_{i,t+1} \geq S^i_{min,t+1}$ and $\sum_{i=1}^m S_{i,t+1} \leq C_{t+1}$, where $C_{t+1}$ is the channel capacity in terms of data-rate at present time instant $(t+1)$.

where, $S_{i,t+1}$ and $S^i_{min,t+1}$ are the tuned data-rate and the disagreement point of $i^{th}$ sensor at time $(t+1)$. The non-negative components $\tau_{i,t}$, $E_i$, $P_{i,t}$, and the positive $CI_{i,t}$ are respectively the total power consumption, the initial power, the probability of failed packet transmission and the criticality index of $i^{th}$ sensor at time $(t+1)$.

Influenced by the utility function model discussed in [16]–[18], we consider criticality index, failure probability and power consumption ratio of the sensors to form the utility function. The properties that the utility function must satisfy are as follows:

1) For fixed failure probability and power consumption ratio, a larger criticality index value $(CI_{i,t})$ implies a larger utility value $(U_i(S_{i,t+1}))$.
2) For fixed criticality index and power consumption ratio, a larger failure probability value $P_{i,t}$ implies a larger utility value $(U_i(S_{i,t+1}))$.
3) For fixed criticality index and failure probability, a larger power consumption ratio $\frac{\tau_{i,t}}{E_i}$ implies a larger utility value $(U_i(S_{i,t+1}))$.

*Theorem 1:* The joint utility set or the feasibility set $S$ is convex.

*Proof:* A set $S$ is convex if $\alpha x + (1-\alpha)y \in S$, for any $x$, $y \in S$, and any $\alpha$ with $0 < \alpha < 1$. In the proposed solution, $S = \{U_1(S_1), U_2(S_2), \ldots, U_m(S_m)\}$. Let $S_A$ and $S_B$ be two different utility points in the joint utility set $S$, such that

$$S_A = \{U_1(a_1), U_2(a_2), \ldots, U_m(a_m)\} \in S. \tag{5}$$

and

$$S_B = \{U_1(b_1), U_2(b_2), \ldots, U_m(b_m)\} \in S. \tag{6}$$

Therefore, the set $S$ is convex if, $\alpha.\, U_i(a_i) + (1-\alpha).\, U_i(b_i) \in S$. From Equation (4), we conclude,

$$S_{i,t+1} = \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}.U_i(S_{i,t+1}) + S^i_{min,t+1}. \tag{7}$$

Therefore,

$$\begin{aligned}\sum_{i=1}^m S_{i,t+1} &= \sum_{i=1}^m \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}.U_i(S_{i,t+1}) + \sum_{i=1}^m S^i_{min,t+1} \\ \Rightarrow C_{t+1} - \sum_{i=1}^m S^i_{min,t+1} &\geq \sum_{i=1}^m \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}.U_i(S_{i,t+1}).\end{aligned} \tag{8}$$

Hence, we express the joint utility set as,

$$S = \left\{ U_i(S_{i,t+1}) \,\middle|\, \sum_{i=1}^m \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}.U_i(S_{i,t+1}) \leq C_{t+1} - \sum_{i=1}^m S^i_{min,t+1}, \forall i \right\}. \tag{9}$$

The convexity of set $S$ holds true, if and only if $f(\alpha) = \sum_{i=1}^m \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}[\alpha U_i(a_i)_{t+1} + (1-\alpha)U_i(b_i)_{t+1}]$ is convex. We conclude that,

$$\sum_{i=1}^m \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}[\alpha U_i(a_i)_{t+1} + (1-\alpha)U_i(b_i)_{t+1}] = \begin{cases} \sum_{i=1}^m \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}.U_i(b_i)_{t+1} & \text{if } \alpha = 0 \\ \sum_{i=1}^m \frac{\frac{\tau_{i(t)}}{E_i} + P_i(t)}{CI_i(t)}.U_i(a_i)_{t+1} & \text{if } \alpha = 1 \end{cases}. \tag{10}$$

$f(\alpha)$ is non-negative when $\alpha = 0$ and 1, as $U_i(a_i)_{t+1}$ and $U_i(b_i)_{t+1}$ are non-negative values. To show that $f(\alpha)$ is convex, we also need to prove that the second-derivatives of $f(\alpha)$ are also non-negative, for all $0 < \alpha < 1$. Let the $i^{th}$ term of $f(\alpha)$ is denoted by $f_i(\alpha)$. Therefore,

$$\frac{d^2 f_i(\alpha)}{d\alpha^2} = \frac{d}{d\alpha}\left[\frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}}.U_i(a_i)_{t+1} - U_i(b_i)_{t+1}\right] \tag{11}$$

Hence, the function $f_i(\alpha)$ is convex. As the sum of convex functions is also convex, $f(\alpha)$ is convex. This concludes the proof. □

The pair $(S, S_{min})$ mathematically defines the bargaining problem among $m$ selected sensors. We also need to understand the concept of *Pareto optimality*. We first define the notion of Pareto-optimal point, and then list the axioms stated by Nash on the bargaining problem.

*Definition 5. (Pareto Optimal Point):* The solution point $(X_1,\ldots,X_n)$ of the bargaining problem $(S,S_{min}) \to \mathbb{R}^n$ is said to be Pareto optimal, if and only if there is no other allocation $X_i' \in S$ exists, such that $X_i' > (S,S_{min}) \to \mathbb{R}^n$. [19]

It is impossible to find any other allocation that leads to better performance for some players.

As it is a scenario where more than two sensors can participate in the bargaining game, therefore, it is possible to have an infinite number of Pareto optimal points [14].

Among the many other solutions in cooperative game theory, NBS provides a unique Pareto optimal solution under certain conditions, as stated below. In the context of the bargaining problem, Nash stated some axioms [17], which must be satisfied by the bargaining solution.

We assume $F$ to be a function $F:(S,S_{min}) \to \mathbb{R}^n$ representing the bargaining solution. This solution can be written as the following optimization function.

$$F(S_1,S_2) = \left(S_1 - S^1_{min}\right)\left(S_2 - S^2_{min}\right). \tag{12}$$

where $(S_1,S_2) \in S$.

$F$ must satisfy the following axioms [17].

1) *Pareto Efficiency*.
2) *Symmetry*.
3) *Invariance or independence of linear transformation*.
4) *Independence of irrelevant alternatives*.

Axioms 2, 3, and 4 are referred to as the *axioms of fairness*. The necessary evidences, which prove that our bargaining solution satisfies these four axioms, are given below.

*Lemma 1:* The proposed bargaining solution $F = (S,S_{min})$ satisfies Pareto optimality.

*Proof:* Let there exist a solution $(S_1',S_2') \in S$ such that $S_1' > S_1$ and $S_2' > S_2$. From Equation (12), we conclude that $F(S_1,S_2) > F(S_1',S_2')$. Therefore, $(S_1,S_2)$ cannot optimize $F$, if there exist $(t_1,t_2) \in S$ with $t_1 > S_1$ and $t_2 > S_2$. This concludes the proof. □

*Lemma 2:* The proposed bargaining solution $F = (S,S_{min})$ is symmetric in nature.

*Proof:* Let $(S_1^*,S_2^*) \in S$ maximize $F$ over $S$. Therefore, we can write,

$$\left(S_1^* - S^1_{min}\right)\left(S_2^* - S^2_{min}\right) \geq F(S_1,S_2)\ \forall (S_1,S_2) \in S. \tag{13}$$

If $F(S,S_{min})$ is symmetric, then the minimum demands of two sensors will be the same, i.e., $S^1_{min} = S^2_{min}$. Therefore, interchanging these two values in Equation (13) we get,

$$\left(S_1^* - S^2_{min}\right)\left(S_2^* - S^1_{min}\right) \geq F(S_1,S_2)\ \forall (S_1,S_2) \in S. \tag{14}$$

Equation (14) implies that $(S{*}_2,S{*}_1)$ also maximizes $F$ over $S$. Therefore, $(S_1^*,S_2^*) = (S_2^*,S_1^*)$, or, $S_1^* = S_2^*$. This concludes the proof. □

*Lemma 3:* The proposed bargaining solution $F = (S,S_{min})$ is independent of linear transformation.

*Proof:* Let $(S',S'_{min})$ be a linear transformation of the bargaining problem $(S,S_{min})$, where $S_i' = \alpha_i S_i + \beta_i$, and $S'^i_{min} = \alpha_i S^i_{min} + \beta_i$, and $\alpha_i > 0$. Therefore,

$$\begin{aligned} F&\left(S_1',S_2'\right) \\ &= \left(S_1' - S'^1_{min}\right)\left(S_2' - S'^2_{min}\right) \\ &= \left(\alpha_1 S_1 + \beta_1 - \alpha_1 S^1_{min} - \beta_1\right)\left(\alpha_2 S_2 + \beta_2 - \alpha_2 S^2_{min} - \beta_2\right) \\ &= \alpha_1\alpha_2\ \left(S_1 - S^1_{min}\right)\left(S_2 - S^2_{min}\right) \\ &= \alpha_1\alpha_2\ F(S_1,S_2). \end{aligned} \tag{15}$$

Therefore, the proposed bargaining solution is independent of linear transformation. □

*Lemma 4:* The proposed bargaining solution $F = (S,S_{min})$ is independent of irrelevant alternatives.

*Proof:* Let there be two bargaining problems $(S,S_{min})$, and $(S',S_{min})$, such that $S' \subseteq S$. If $F(S,S_{min}) \in S'$, then $F(S',S_{min}) = F(S,S_{min})$. In other words, if bargaining in the utility region $S$ results in a solution $F(S,S_{min})$ that lies in a subset $S'$ of $S$, then a hypothetical bargaining in the smaller region $S'$ results in the same outcome. This concludes the proof. □

*Theorem 2:* There exists a unique solution satisfying the four axioms, and this solution is the pair of utilities $(s_1^*,s_2^*)$ that solves the following optimization problem [17].

$$\underset{(S_1,S_2)}{\arg\max}\ \left(S_1 - S^1_{min}\right)\left(S_2 - S^2_{min}\right). \tag{16}$$

such that, $(s_1,s_2) \in S$ and $(s_1,s_2) \geq (S^1_{min},S^2_{min})$ where, $(s_1 - S^1_{min})(s_2 - S^2_{min})$ is termed as Nash product.

*Proof:* Based on the proofs of Lemmas 1 to 4 we conclude that the proposed bargaining solution satisfies the four axioms stated by Nash. □

If only two sensors participate in bargaining, then Theorem 2 is applicable, directly. But the number of sensors that participate in the game depends on the implementation scenario. Therefore, as we cannot predict it, we extend the convex set $S$ to $m$-dimensions (as we deal with $m$ number of sensors in consideration). Hence, the generalized optimization problem is as follows.

$$\underset{(S_1,\ldots,S_m)}{\arg\max} \prod_{i=1}^{m}\left(S_i - S^i_{min}\right). \tag{17}$$

such that $(S_1,\ldots S_m) \in S$ and $S_i \geq S^i_{min}$, where $S_{min} = (S^1_{min},\ldots,S^m_{min})$ is the set of disagreement points. Evidently, the solution of the Generalized Nash Product (GNP) given in Equation (17) satisfies the axioms provided by Nash in the $m$-dimensional space.

According to Theorem 2, there exists a unique solution $F(S,S_{min})$ that satisfies all the Nash axioms. Equation (18) also satisfies these axioms.

$$F(S,S_{min}) \in \underset{(U_1,\ldots,U_m)}{\arg\max} \prod_{i=1}^{m}\left[U_i(S_{i,t+1}) - S^i_{min,t+1}\right]. \tag{18}$$

subject to $S_{i,t+1} \geq S^i_{min,t+1} \forall i$, and $\sum_{i=1}^{m} S_{i,t+1} = C_{t+1}$, where $C_{t+1}$ denotes the available channel capacity at present time $t+1$.

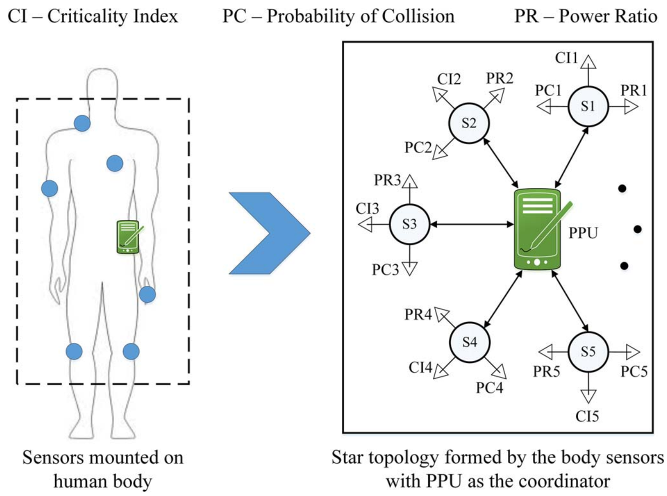



Fig. 1. Architecture.

We solve the optimization problem described in (18) using the Lagrange Multiplier approach and get the generalized solution as follows.

$$S_{i,t+1} = \frac{1}{m} \cdot \left[ C_{t+1} + (m-1) \left( \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}} \right) S^i_{min,t+1} - \sum_{j \neq i}^{m} \left( 1 + \frac{\frac{\tau_{j,t}}{E_j} + P_{j,t}}{CI_{j,t}} \right) S^j_{min,t+1} \right]. \quad (19)$$

This is the solution of the optimization problem stated in Equation (18). The personal processing unit tunes the data-rate of the $i^{th}$ sensor for time $(t+1)$ according to the solution.

Running the necessary computations and tuning data-rates accordingly are the primary responsibilities of the PPU associated with the body sensors.

## V. Analytical Results

For evaluating the performance of the proposed solution, we consider a channel having a limited data-rate capacity of 250 kbps, which is the maximum data transmission rate for ZigBee protocol (IEEE 802.15.4). Throughout the simulation we used the simulation topology illustrated in Fig. 1. It is a star topology in which the body sensor nodes $(S_1, S_2, \ldots, S_n)$ act as the end-devices and the PPU acts as the central coordinator. Duplex communication is possible between a sensor device and the PPU, which analyzes the proposed utility function parameters and tune the data-rate for that sensor accordingly.

### *A. Effect of Utility Function Parameters*

Criticality Index (CI) is a measure of exigency of the sensed physiological data for individual sensors, as defined in Definition 1 in Section III. The proposed model designs the general utility function for all the sensor nodes in such a way that it reflects the consequences of health-criticality on data-rate tuning. We consider constant minimum demands of 5 Kbps, 10 Kbps and 15 Kbps for all sensors and depict the tuned data-rates through Figs. 2 and 3, thus, validate the proposed utility function. When the CI of a particular sensor increases, it also affects the utility value of that sensor, as illustrated in Fig. 3(a), and subsequently, the data-rate also increases.

For a particular CI value we consider several value-sets of data-rates that change based on the other two dynamic parameters—Failure Probability and Power Consumption Ratio. Fig. 2(a) illustrates the average value along with the range (minimum and maximum) of tuned data-rate. We consider 95% confidence interval to find the range of tuned data-rate. Therefore, it is evident from Fig. 2(a), that whenever the PPU detects abnormality in sensed physiological data, it increases the data-rate of that particular sensor. Thus, critical sensors are able to work efficiently at a certain time when they have severe physiological data to transmit to the PPU.

Another parameter in our utility function is the Failure Probability of data transmitted at a certain time, as defined in Definition 2 in Section IV. Successful data reception by the LPU may fails due to collision of simultaneously transmitted packets or due to some channel errors. Therefore, this parameter should be taken into account while designing the utility function. We contemplate this as a negative reputation for the sensor at that particular time-span. Fig. 2(b) depicts the nature of relation between the tuned data-rate and the probability of collision. High failure probability of a particular sensor at a certain time indicates something abnormal in the communication associated with that sensor. It also incurs high energy expenditure due to several re-transmission efforts. Therefore, if that sensor does not possess critical physiological data at that time, the PPU tries to reduce the data-rate allocated to that sensor.

Thus, as the failure probability increases, the tuned data-rate should decrease in general. However, exceptions are possible due to the effect of other two parameters—Criticality Index and Power Consumption Ratio. We consider constant minimum demands for all sensors in our experiments while the other two parameters are considered as variables. Accordingly we observe an overall decrease in utility contribution as depicted in Fig. 3(b) while probability of failure increases. Therefore, data-rate also decreases with the increment of failure probability, as penalty charges due to packet failures. We plot the average, minimum and maximum values of data-rates with 95% confidence interval in Fig. 2(b) for minimum demands of 5 Kbps, 10 Kbps and 15 Kbps.

We also consider the Power Consumption Ratio as a parameter of utility function that has a similar relation with the tuned data-rate. It is defined in Definition 3 in Section IV We consider that the transmission power of a sensor node is directly proportional to the data-rate associated with it at a particular time. Therefore, it is necessary to consider the power consumption ratio as a part of the utility value. The sensors that loose power in a comparatively high rate should not be assigned with high data-rates. If the sensors do not posses critical physiological data at a certain time, the PPU reduces its data-rate and assign some other needy sensors with higher data-rate to balance the overall network performance. Thus, the tuned data-rate is inversely proportional to the power consumption ratio in the proposed model, which is illustrated in Fig. 2(c) with 95% confidence interval. Fig. 3(c) illustrates the amount of contribution to the overall utility value by this parameter.

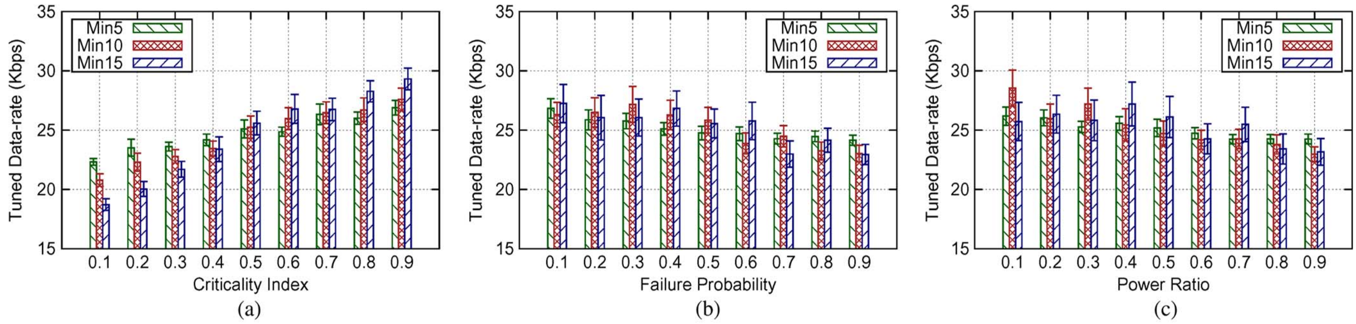



Fig. 2. Data rate vs. attributes of utility function. (a) Data-rate vs. criticality index. (b) Data-rate vs. failure probability. (c) Data-rate vs. power consumption ratio.

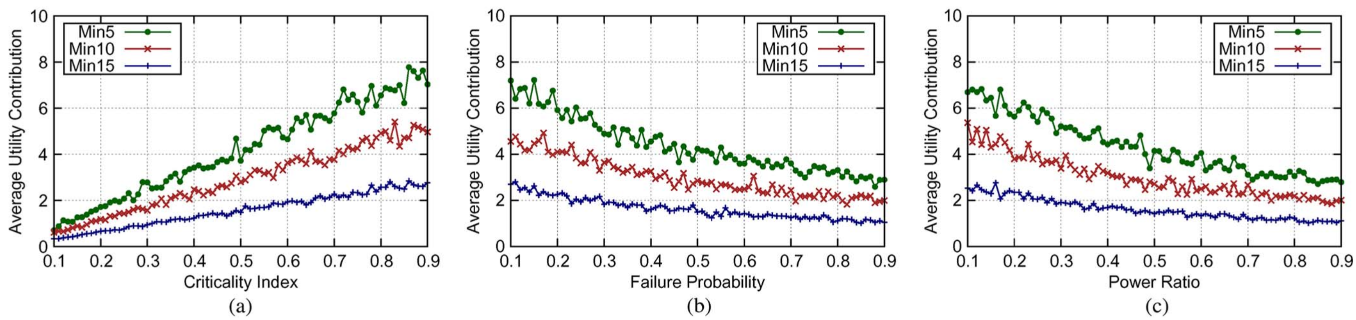



Fig. 3. Attributes' contribution to utility value. (a) Contribution of criticality index. (b) Contribution of failure probability. (c) Contribution of power consumption ratio.

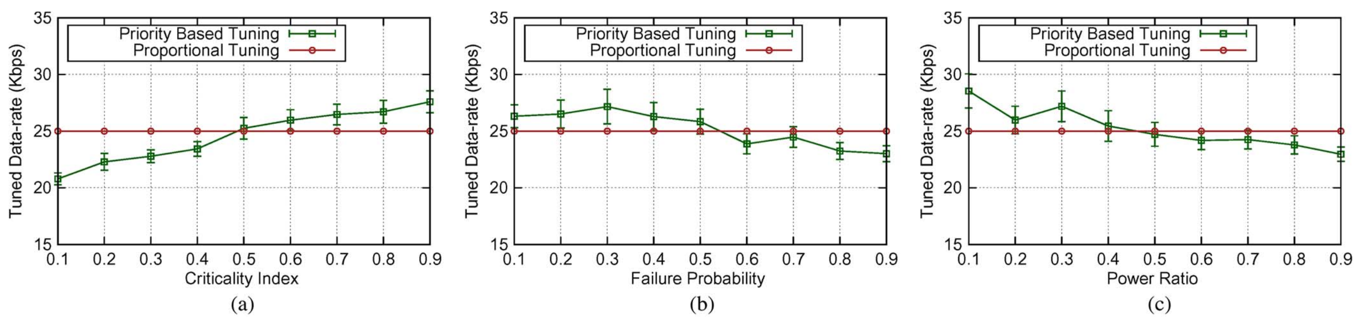



Fig. 4. Priority-based tuning vs. proportional tuning. (a) Effect of criticality index. (b) Effect of failure probability. (c) Effect of power consumption ratio.

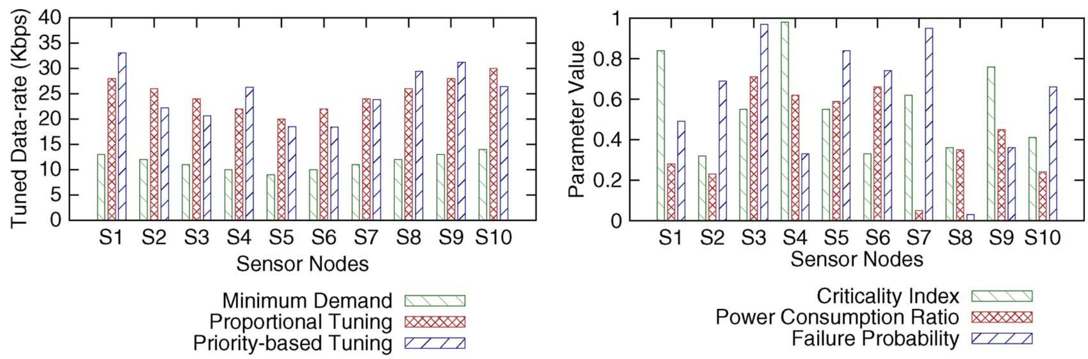
### *B. Comparison of Priority-Based Tuning With Proportional Tuning*

The comparison between proportional tuning and priority-based tuning with respect to a constant minimum demand is illustrated in Fig. 4. If the minimum demands of all the sensor nodes are the same, then the proportional tuning method results in a constant allocation of data-rate irrespective of the health condition of a physiological parameter, the packet transmission failure tendencies and the energy expenditure of a particular sensor. However, Fig. 4(a)–(c) depict that priority-based tuning provides an effective allocation result by considering utility function and its parameters. When sensed data are critical then the allocation of data-rate for that sensor is high, as depicted in Fig. 4(a). This approach, which was not addressed in proportional tuning, is very useful in case of emergency healthcare scenarios.

Similarly, we also compare the proposed method with respect to the failure probability and the power ratio of a sensor and get effective results, illustrated by Fig. 4(b) and (c), respectively. When failure probability or power ratio of a particular sensor node increases, the data-rate allocation decreases. In all the subfigures of Fig. 4, we consider a single parameter as independent variable, while other parameters take different values within the possible range. We consider 60 such results and plot a single result with 95% confidence interval.

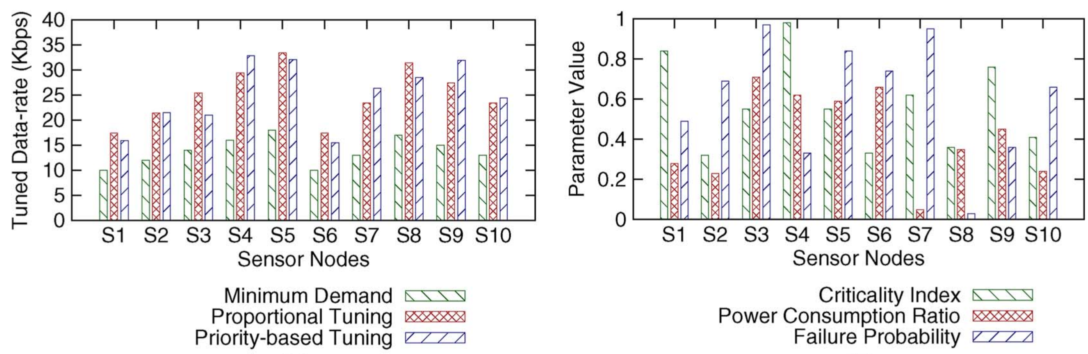
### *C. Data-Rate Allocation With Two Different Sets of Minimum Demands*

In the proposed model, rather than tuning data-rate proportionally, we incorporate a bargaining game among the sensors. Figs. 5(a) and 6(a) illustrate the tuning result for two different sets of minimum demands, and Figs. 5(b) and 6(b) show the corresponding values of the parameters used in the utility function. From Fig. 5(a) it is evident that the data-rate values in case of proportional tuning are linearly dependent on the minimum demand values of each sensor, whereas in case of priority-based tuning, the data-rate also depends on the utility function parameter values depicted in Fig. 5(b). According to Fig. 5(b), sensors S1, S4, and S9 have significantly high critical physiological-data to transmit. The power consumption ratio and probability of packet failure are moderate for these sensors. Therefore, as a combined effect of these three, the proposed priority-based model tunes the data-rate of these three sensors. We achieve 13.67% average increase in data-rates for S1, S4 and S9, as illustrated in Fig. 5(a).



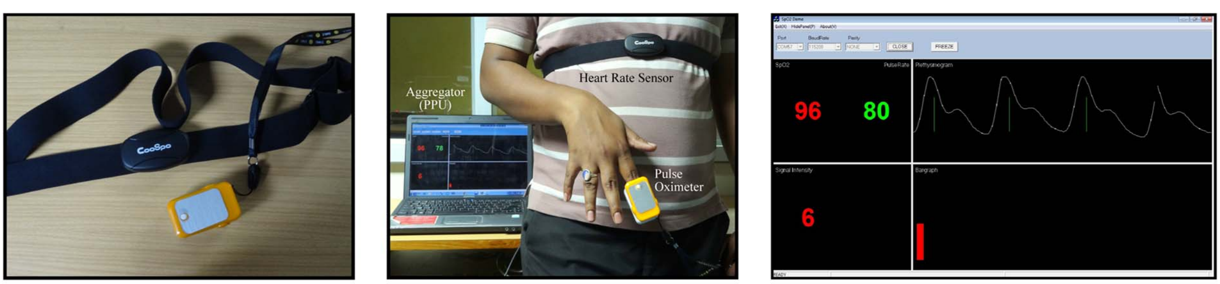

(a) (b)

Fig. 5. Data-rates comparison and Parameter values for Set 1 Minimum demand. (a) Priority-based tuning vs. proportional. (b) Parameter values for priority-based tuning.




(a) (b)

Fig. 6. Data-rates comparison and parameter values for set 2 minimum demand. (a) Priority-based tuning vs. Proportional. (b) Parameter values for Priority-based Tuning.




(a) (b) (c)

Fig. 7. Real system implementation. (a) Wireless network setup. (b) Sensors. (c) Screenshot.

Fig. 6(b) illustrates that the sensors S4, S5, and S9 are critical in terms of physiological data. In this case, the proposed model achieves 7.47% average increase in data-rates, which is marginally lesser than the previous experiment, due to the high power consumption ratio and failure probability associated with these three sensors.

Figs. 5 and 6 depict the relations of utility function parameters with data-rate tuning mechanism. From these figures it is evident that proportional tuning is not sufficient until we do not consider a proper utility function for body sensor devices. These plots also depict how much the parameters contribute to the utility function.

## VI. Real System Implementation

We practically implement the proposed work using Bluetooth-enabled real sensors, as illustrated in Fig. 7. We employ a heart rate sensor and a pulse oximeter sensor to validate the proposed model, as depicted in Fig. 7(a). The specification details of the pulse-oximeter sensor is described in Table I in details. The heart rate sensor is attached to the chest through a belt and the pulse oximeter is attached to the index finger of the right hand as depicted in Fig. 7(b). One laptop is being used as an aggregator or PPU as described in Section III. The screenshot of the aggregator provided in Fig. 7(c) depicts

TABLE I
SPECIFICATION

| Attributes | | Description |
|---|---|---|
| Measurement Range | $SpO_2$ | $0-100\%$ |
| | Pulse Rate | $25-250$ bpm |
| Resolution | $SpO_2$ | $1\%$ |
| | Pulse Rate | 1 bpm |
| Accuracy | $SpO_2$ | $\pm 2\%(70-100\%)$ |
| | Pulse Rate | $\pm 1\%(25-250)$ bpm |
| Input Voltage | | 3 V |
| Input Current | | $< 40$ mA |

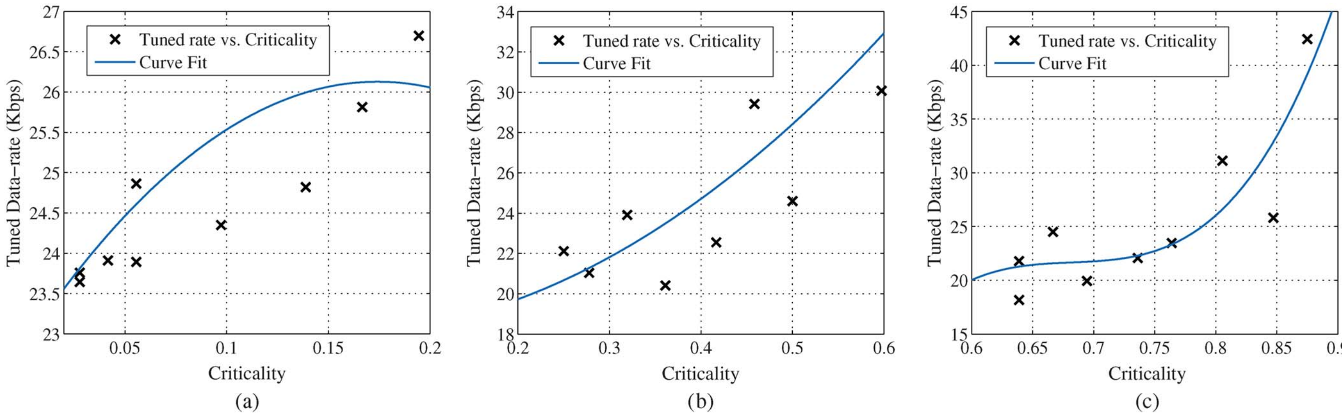



Fig. 8. Different stages of pulse rate criticality. (a) Criticality—low. (b) Criticality—medium. (c) Criticality—high.

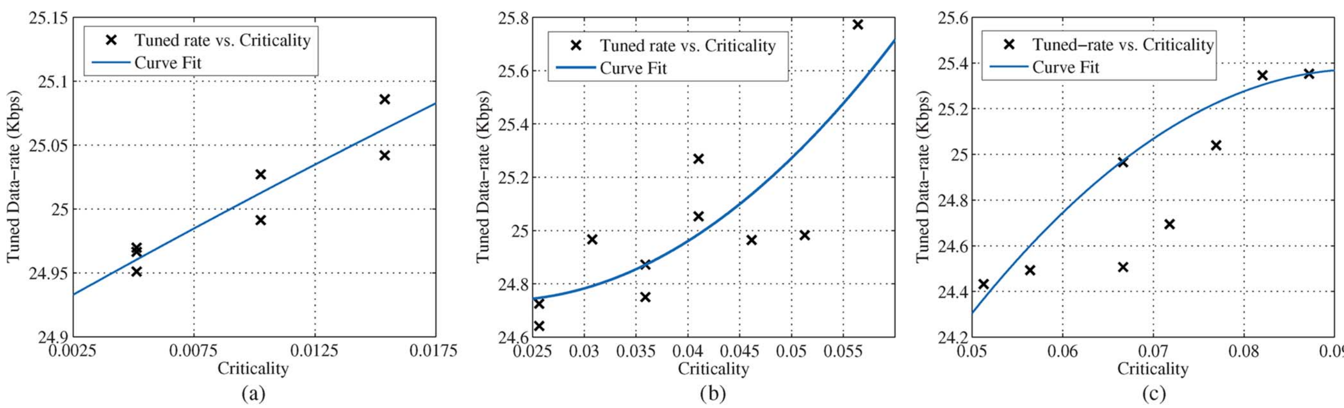



Fig. 9. Different stages of $SpO_2$ criticality. (a) Criticality—low. (b) Criticality—medium. (c) Criticality—high.

the sensed pulse rate value, $SpO_2$ value, signal strength, and Plethysmogram respectively. Inspired by the work of Zhen *et al.* [20] we also plan to develop an android application as an aggregator, so that we can comfortably use a mobile phone as the PPU in place of a laptop. We consider sample dataset having diverse range of pulse rate readings and blood oxygen saturation ($SpO_2$) readings. We acknowledge the normal readings of pulse rate and $SpO_2$ as 72 bpm and 97.5% respectively.

Due to the unavailability of real hospital data, it is very difficult to create an scenario that yields *critical* physiological readings. However, we manage to cover the full range of criticality index by artificially creating scenarios. We collect data associated with three different stages of physical activities. Along with normal condition, we also consider pulse rate readings after light work and heavy exercise to get higher criticality index values. We further divide the whole range of criticality index into three stages and plot the curve-fit of the corresponding tuned data-rates as represented in Fig. 8. Three different stages of criticality are addressed in Fig. 8(a)–(c). In all of them the tuned data-rates increase with the increment of criticality index. Especially, in Fig. 8(c), the steep rise in tuned data-rate corresponding to very high criticality index justifies the proposed assessment.

In case of $SpO_2$, we follow the same approach to capture longer range of criticality index. However, it is not practically feasible to get very low oxygen saturation in blood, through artificial scenarios. Therefore, we divide the range of 0 to 0.1 into three stages and plot the pattern of tuned data-rate with respect to the change of criticality index, as depicted in Fig. 9. Fig. 9(a)–(c) represent the curve-fits of data-rate tuning with the increment of criticality index.

Therefore, the above results conform with the analytical results provided in Fig. 4(a) in Section V. The interesting observation is that the pattern of tuned data-rate depends on the increment of criticality index. The changes in the lower bound and the upper bound do not affect the pattern of data-rate tuning.

## VII. Conclusion

In this paper, we proposed a solution to the problem of priority-based data-rate tuning in a wireless body area network based on the Nash Bargaining Solution. The proposed approach tune the data-rates based on certain parameters such as—Criticality Index, Failure Probability, Power Consumption Ratio, along with the minimum demands of the sensors. Evidently, this approach leads to a better tuning that specially takes care of the criticality of measured physiological data, through increasing the data-rate for critical sensor nodes by 10% on average. The achievements are also validated through real system implementation. In future, we plan to consider selfish behavior of body sensor nodes and wish to expand this novel work by introducing dynamic bargaining power as a positive or negative reward function for each sensors.

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