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 applications, having critical importance in providing useful 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 Nash Bargaining Solution (NBS), which not only provides 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.

Index Terms

Wireless Body Area Network (WBAN), Bargaining Power, Generalised Nash Bargaining Solution (NBS), Cooperative Game, Data-rate Tuning.

I. INTRODUCTION

Advances in micro-electro-mechanical systems (MEMS), wireless communications, and digital technologies have opened up different areas for research, among which Wireless Body Area Networks (WBANs) is one of the most emerging ones. Low-cost, ultra-low-power, multifunctional tiny sensor nodes in WBANs deliver innovative approaches towards intelligent health monitoring services such as post-operative care in hospitals and ubiquitous treatment of aged persons at home. These sensors continuously monitor patients' physiological activities, and motions, and provide real-time feedback to the users or medical supervisors [1]. 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 the monitoring unit. 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 [2]. Therefore, tuning the data-rate of the sensors is fundamentally prudent.

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. In order to address this problem, 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. We envision that the body sensor nodes cooperate with one another in a bargaining process, and the associated Personal Processing Unit (PPU) manages the joint agreements between them to fine-tune their data-rates.

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 envision the necessity of prioritize the sensors while tuning the data-rates for them. Consequently, we incorporate the concepts of utility function and co-operative game theory in the proposed work.
- We contemplate the involvement of health, network and sensor characteristics using different parameters, while designing the utility function for the sensors.

II. Related Works

While there is deficiency of work on data-rate tuning in WBANs, there exists some relevant ones, which are mentioned here. Pohl et al. [3] analyzed the trade-off between data-rate and interference reduction capability of the system. With sufficient evidences they have shown the necessity of fine tuning of data-rates for application in the 2.45 GHz ISM band. A proper choice of data rate can also minimize signal to interference ratio. Lin and Hou [4] the authors have discussed an important issue of balancing spatial reuse and data transmission rate. They provided an analytical model for IEEE 802.11 and estimated the amount of interference created and the corresponding SINR due to concurrent transmissions. Based on the SINR value they further evaluate the optimal data transmission rate. Misra and Sarkar [5] 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 [6] 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. However, they do not consider the criticality of physiological parameters while determining the data rate of a sensor at a certain time instance.

The approach of resource bargaining was also explored in the past for solving problems in different network domains. For instance, Liang et al. [7] developed dynamic resource allocation schemes with incomplete information, based on online test-optimization strategy. In [8], the concepts of Pareto optimality and NBS are used to design an inter-domain traffic engineering protocol. In this work, ISPs use an iterative procedure to jointly optimize a social cost function, referred to as the Nash product. Mazumder et al. [9] used the concept of bargaining in the context of packet-switched networks. Some interesting studies of Pareto optimality and local optimization procedures are presented in this paper. Kelly [10] and Kelly et al. [11] 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. Douligeris and Mazumder [12]designed a game theoretic approach for studying the flow control problem. Chen et al. [13] derived the sufficient condition for the uniqueness of the Nash Bargaining Solution in multiple-input multiple-output (MIMO) interference channels (IFCs). Jiang and Howitt [14] proposed a multi-domain load balancing scheme to adaptively balance resource utilization and co-channel interference. Hew and White [15] applied the concept of NBS and proposed symmetric and asymmetric models for resource bargaining among the users and mobile virtual network operators. Qian et al. [16] proposed an NBS-based relay power allocation scheme in a multi-user single-relay wireless network. Optimum resource allocation in a secondary spectrum access scenario is developed by Attar et al. [17] with the help of NBS. Game theoretic approach such as pure strategy Nash Equilibrium is also used in [18] for distributed channel selection to mitigate interference in cognitive radio networks (CRNs).

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, for reasons featured below.

- Body sensor nodes in a WBAN are heterogeneous in nature, and they deal with physiological parameters of a patient, whereas the terrestrial sensor nodes in a WSN are typically homogeneous in nature, and mostly concern environmental changes.
- There exists the necessity of considering the unique features of heterogeneous body sensor nodes to design an efficient utility function in a WBAN.
- The rate of energy harvesting from environment in WBANs is not comparable to that in WSNs. Thus, energy constraint plays a vital role in such a network.
- Criticality of sensed physiological data is an important measure in designing the utility function in WBANs, which is typically not considered in normal WSNs.

The proposed cooperative game theoretic approach considers WBAN-specific problems and addresses the issues of 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 effectively transmit and transform the sensed data into valuable information while meeting other criteria such as energy and computational efficiency.

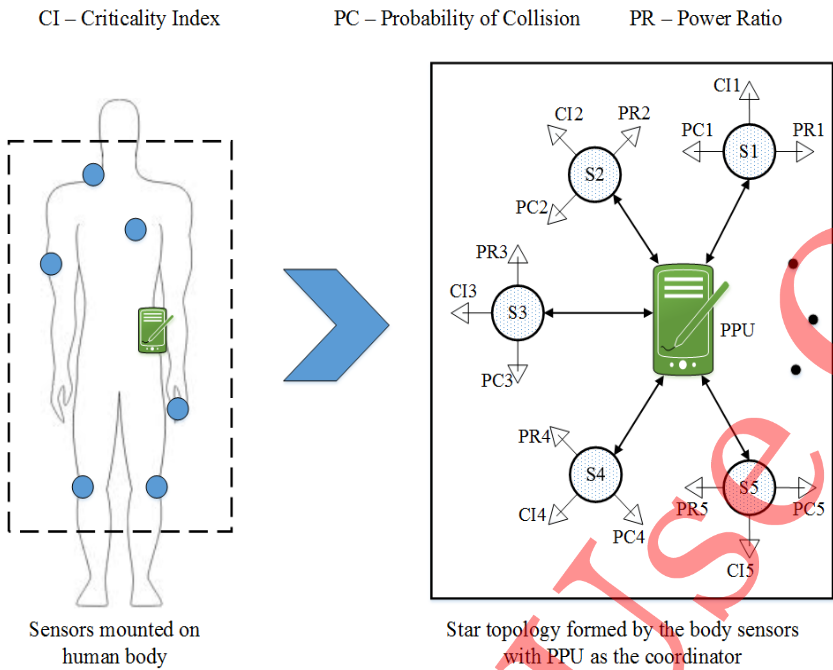


Fig. 1: Architecture

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 [19]. In a Star network all, peripheral nodes connect to the PPU, which allows for high data throughput and, thus, simplified routing. However, the disadvantage is in having a central coordinator, because these are more prone to single-point failure. A Star-Mesh hybrid topology extends the traditional star approach, and creates mesh networks among central coordinators in multiple star networks.

Another challenge in body area networking is the heterogeneity of sensor nodes. Different sensors exhibit differences in transmitted data rates [20]. 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 in order to improve 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 collisions, and energy expenditures while optimizing the data rate for a particular sensor. We propose some definitions for each sensor to estimate various relevant 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 for the i^{th} sensor is,*

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

where, ξ_s is the sensed measurement through the i^{th} sensor, and ξ is the normal value for the corresponding physiological parameter.

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

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

In this paper we propose a priority-based dynamic tuning mechanism, In order to do so we incorporate a cooperative game theoretic approach based on the Nash Bargaining Solution (NBS) [21]–[23].

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*.

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 is denoted by $U_i(S_i)$, where *i* = 1, 2,..., m. Therefore, we get a closed set to represent all possible utilities

TABLE I: Notations

Notation	Description
S	Feasible utility set
$S_{i,t}$	Tuned data-rate of i^{th} sensor at time instance t
$S^i_{min,t}$	Disagreement point of i^{th} sensor at time instance t
$U_i(S_i)_t$	Utility function value of i^{th} sensor at time t
$\tau_{i,t}$	Total power consumption of i^{th} sensor at time t
E_i	Initial power of i^{th} sensor
$P_{i,t}$	Probability of collision of packets transmitted from i^{th} sensor at time t
$CI_{i,t}$	Criticality Index of i^{th} sensor at time instance t

of participating sensors. Let it is denoted by *S*.

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

The set *S* is known as the *joint utility set* or a *feasible utility set* [24].

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,..., m. Furthermore, the set of disagreement points for each player is defined as:

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

The fundamental challenge in the problem is to design the utility function for the sensors that participate in bargaining. Each sensor implanted over a patient's body is assigned a particular data transmission rate by the PPU associated with that patient according to a certain utility function. The overall network behavior is a cumulative result of data transmissions from all these sensors. Therefore, efficient design of utility function is always of prime concern.

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

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

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 $(t+1)$.

For reader's convenience, we summarize the notations used in this Section in Table I.

Lemma 1. *The utility values associated with each sensor is always non-negative.*

Proof. From Equation 4, we conclude that the utility value of the i^{th} sensor cannot be less than zero. The parameters used to form the utility function, such as $\tau_{i,t}$, E_i, $P_{i,t}$, are all non-negative components and $CI_{i,t}$ is a positive component. Zero is the minimum value these parameters can take. Therefore, the one and only condition that renders utility value negative is $S_{i,t+1} < S_{min,t+1}$. However, this is not possible, because $S^i_{min,t+1}$ is the minimum requirement of the i^{th} sensor at time instant $(t+1)$. Hence, the assigned data-rate to the i^{th} sensor, i.e., $S_{i,t+1}$ cannot be less than $S^i_{min,t+1}$. This concludes the proof. □

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 α with $0 < \alpha < 1$. In the proposed solution, $S = \{U_1(S_1), U_2(S_2), ..., U_m(S_m)\}$. Let S_A and S_B be two different utility points in the joint utility set *S*, such that

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

and

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

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,

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

Hence, we express the joint utility set as,

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

To prove the convexity of set S, we have to show that, $f(\alpha) = \sum_{i=1}^{m} \frac{\frac{\tau_{i,t}}{E_i}+P_{i,t}}{CI_{i,t}} [\alpha U_i(a_i)_{t+1} + (1-\alpha)U_i(b_i)_{t+1}]$ is convex. We conclude that,

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

$f(\alpha)$ 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 (see Lemma 1). 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,

$$\begin{aligned} \frac{df_i(\alpha)}{d\alpha} &= \frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}} . U_i(a_i)_{t+1} - U_i(b_i)_{t+1} \\ \Rightarrow \frac{d^2 f_i(\alpha)}{d\alpha^2} &= 0 \end{aligned} \tag{11}$$

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 $(X_1, ..., X_n) \in S$ is said to be Pareto optimal, if and only if there is no other allocation $X_i' \in S$, such that $X_i' \geq X_i, \forall i$, and $X_i' > X_i, \exists i$ [24].*

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 infinite number of Pareto optimal points [21]. In our problem, m sensors participate in the bargaining game, and therefore, an $(m-1)$ dimensional hyper-surface is always formed by the

Pareto optimal points. Evidently, it implies that there exists infinite number of Pareto optimal points. Therefore, choosing a single Pareto optimal point which maximizes the gains of each sensor should be another outcome of the bargaining solution.

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 [24], which must be satisfied by the bargaining solution.

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

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

where $(S_1, S_2) \in S$.
F must satisfy the following axioms [24].

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

Proof. Let $(S^*_1, S^*_2) \in S$ maximizes *F* over *S*. Therefore, we can write,

$$(S^*_1 - S^1_{min})(S^*_2 - S^2_{min}) \geq F(S_1, S_2) \forall (S_1, S_2) \in S. \tag{13}$$

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,

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

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 4. *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,

$$\begin{aligned} F(S'_1, S'_2) &= (S'_1 - S'^1_{min})(S'_2 - S'^2_{min}) \\ &= (\alpha_1 S_1 + \beta_1 - \alpha_1 S^1_{min} - \beta_1)(\alpha_2 S_2 + \beta_2 - \alpha_2 S^2_{min} - \beta_2) \\ &= \alpha_1 \alpha_2 \, (S_1 - S^1_{min})(S_2 - S^2_{min}) \\ &= \alpha_1 \alpha_2 \, F(S_1, S_2) \end{aligned} \tag{15}$$

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

Lemma 5. *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 [24].*

$$\arg\max_{(S_1, S_2)} (S_1 - S^1_{min})(S_2 - S^2_{min}) \tag{16}$$

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 2 to 5 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.

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

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.

V. Data-rate Tuning

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.

$$F(S, S_{min}) \in \arg\max_{(U_1,\ldots,U_m)} \prod_{i=1}^{m} U_i(S_i)_{t+1} - S^i_{min,t+1}. \tag{18}$$

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 instance $t+1$.

We solve the optimization problem described in Equation (18) using the Lagrange Multiplier approach. The Lagrange Function in this problem is as follows.

$$L(S_1, S_2, \ldots., S_m) = \prod_{i=1}^{m} \left[U_i(S_i)_{t+1} - S^i_{min,t+1}\right] - \lambda \left[\sum_{i=1}^{m} S_{i,t+1} - C_{t+1}\right] \tag{19}$$

where, λ is the Lagrange Multiplier.

The generalized partial derivative corresponding to the Lagrange Function with respect to S_i is given below.

$$L(S_{i,t+1}) = \frac{\partial L(S_{1,t+1}, S_{2,t+1}, ..., S_{m,t+1})}{\partial S_{i,t}}$$
$$= \frac{CI_{i,t}}{\frac{\tau_{i,t}}{E_i} + P_{i,t}} . \prod_{j \neq i}^{m} \left[\frac{CI_{j,t}}{\frac{\tau_{j,t}}{E_j} + P_{j,t}} . \left(S_{j,t+1} - S^j_{min,t+1} \right) S^j_{min,t+1} \right] - \lambda$$
$$= 0 \tag{20}$$

Similarly, the partial derivative with respect to λ is given below.

$$L(\lambda) = \frac{\partial L(S_{1,t+1}, S_{2,t+1}, ..., S_{m,t+1})}{\partial \lambda}$$
$$= C_{t+1} - \sum_{i=1}^{m} S_{i,t+1} = 0. \tag{21}$$

After solving the corresponding partial derivatives $L(S_{1,t+1}), L(S_{2,t+1}), ..., L(S_{m,t+1})$ obtained from Equation (20) and (21), we get the generalized solution as follows.

$$S_{i,t+1} = \frac{1}{m} . \left[C_{t+1} + (m-1) \left(\frac{\frac{\tau_{i,t}}{E_i} + P_{i,t}}{CI_{i,t}} \right) S^i_{min,t+1} - \sum_{j \neq i}^{m} \left(1 + \frac{\frac{\tau_{j,t}}{E_j} + P_{j,t}}{CI_{j,t}} \right) S^j_{min,t+1} \right] \tag{22}$$

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 instance $(t+1)$ 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. The PPU gathers necessary information of each sensors such as – Criticality Index, Collision Probability, and Power Consumption Ratio and computes the utility function as described in the previous Section. Based on the utility values and the minimum demands of each sensors, the PPU tunes the data-rate of individual sensors in a way, such that the sensors' demand get satisfied and also the network yields an optimal performance.

VI. Analytical Results

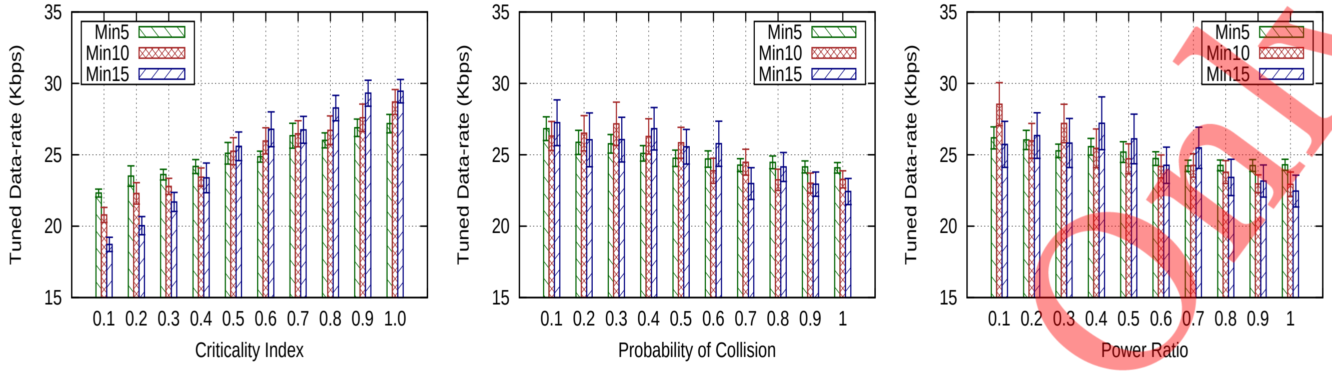
For evaluating the performance of the proposed solution, we consider a channel having a limited data-rate capacity of 250 kbps, which is the maximum data transmission rate for ZigBee protocol (IEEE 802.15.4). Throughout the simulation we used the simulation topology illustrated in Figure 1. It is a star topology in which the body sensor nodes $(S_1, S_2, ..., S_n)$ 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.

First, we briefly discuss the nature of the proposed data-rate tuning model with respect to the parameters of utility function used in this model, such as Criticality Index, Collision Probability, and Power Consumption Ratio. Then we compare the proposed priority-based model with Proportional Tuning method and show that the proposed model yields better result for the sensors that have critical physiological data to transmit. We also provide two experimental results for ten body sensors having two different sets of minimum demands. We plot data-rate allocations and the values of the utility function's parameters to show the overall relationship among them. Lastly, we discuss the importance of considering utility function and a co-operative game theoretic approach in order to achieve a priority-based data-rate tuning method in WBANs.

A. *Effect of Utility Function Parameters*

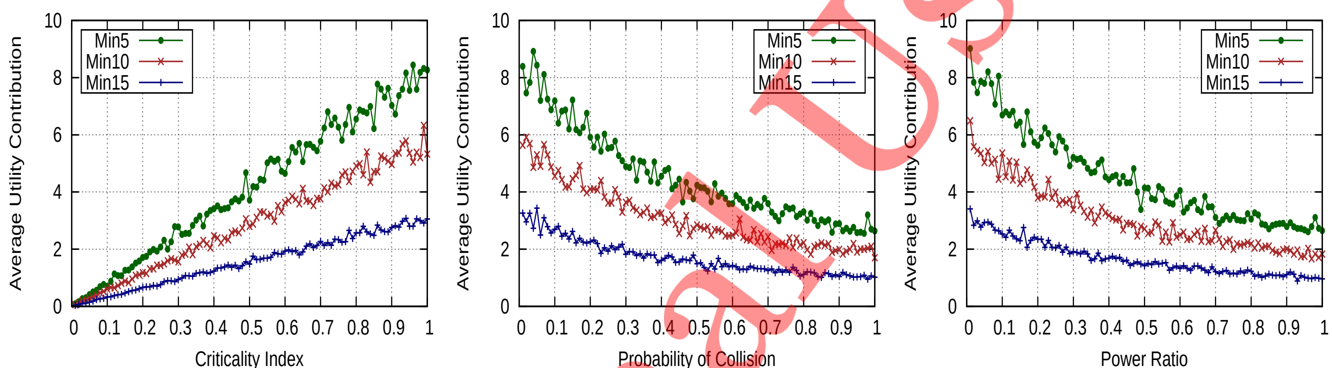
Criticality Index (CI) is a measure of exigency of the sensed physiological data for individual sensors, as defined in Definition 1 in Section III. The proposed model designs the general utility function for all the sensor nodes in such a way that it reflects the consequences of health-criticality on 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 Figure 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 Figure 3(a), and subsequently, the data-rate also increases. For a particular CI value we consider several value-set of data-rates that change based on the other two dynamic parameters – Collision Probability and Power Consumption Ratio. Figure 2(a) illustrates the average value along with the range (minimum and maximum) of tuned data-rate. We consider 95% confidence interval in order to find the range of tuned data-rate. Therefore, it is evident from Figure 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 Collision Probability of data transmitted at a certain time, as defined in Definition 2 in Section IV. When data transmission by a particular sensor suffers from collision due to some channel errors, then 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. Figure 2(b) depicts the nature of relation between the tuned data-rate and the probability of collision.



(a) Data-rate vs Criticality Index (b) Data-rate vs Collision Probability (c) Data-rate vs Power Consumption Ratio

Fig. 2: Data Rate vs. Attributes of Utility Function

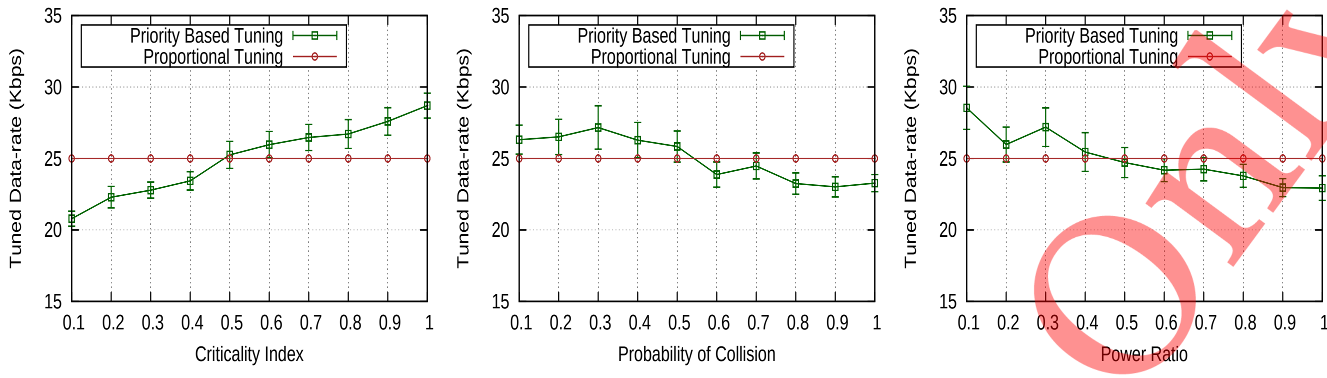


(a) Contribution of Criticality Index (b) Contribution of Collision Probability (c) Contribution of Power Consumption Ratio

Fig. 3: Attributes' Contribution to Utility Value

High collision 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 do not posses critical physiological data at that time, the PPU tries to reduce the data-rate allocated to that sensor. Thus, as the collision 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 Figure 3(b) while probability of collision increases. Therefore, data-rate also decreases with the increment of collision probability. We plot the average, minimum and maximum values of data-rates with 95% confidence interval in Figure 2(b) for minimum demands of 5 Kbps, 10 Kbps and 15 Kbps.

We also consider Power Consumption Ratio as a parameter of utility function that has a similar relation



(a) Effect of Criticality Index (b) Effect of Collision Probability (c) Effect of Power Consumption Ratio

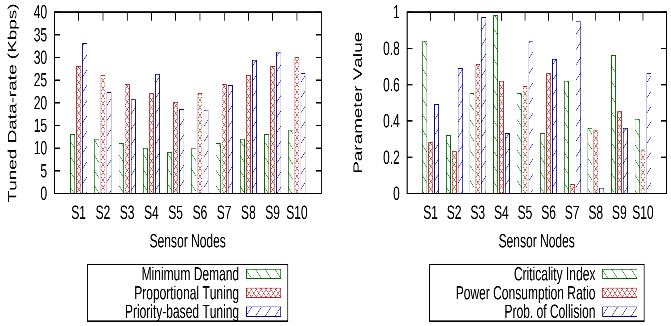
Fig. 4: Pririty-based Tuning vs. Proportional Tuning

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 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 Figure 2(c) with 95% confidence interval. Figure 3(c) illustrates the amount of contribution to the overall utility value by this parameter.

B. Comparison of Priority-based Tuning with Proportional Tuning

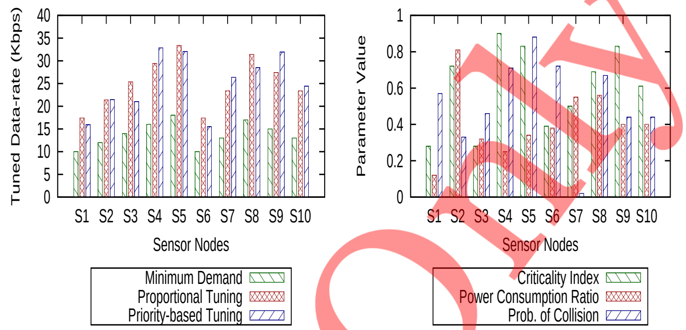
The comparison between proportional tuning and priority-based tuning with respect to a constant minimum demand is illustrated in Figure 4. If the minimum demands of all the sensor nodes are same then proportional tuning method results into a constant allocation of data-rate irrespective of the health condition of a physiological parameter, the packet collision tendencies and the energy expenditure of a particular sensor. However, Figures 4(a) to 4(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 Figure 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 collision probability and the power ratio of a sensor and get effective results, illustrated by Figure 4(b) and 4(c), respectively. When collision



(a) Tuning Comparison (b) Parameter values

Fig 5. Comparison for Set 1 Minimum demand



(a) Tuning Comparison (b) Parameter values

Fig 6. Comparison for Set 2 Minimum demand

probability or power ratio of a particular sensor node increases, the data-rate allocation decreases. In all the sub-figures of Figure 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 incorporates a bargaining game among the sensors. Figures 5(a) and 6(a) illustrate the tuning result for two different sets of minimum demands, and Figure 5(b) and 6(b) show the corresponding values of the parameters used in the utility function. From Figure 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 Figure 5(b). According to Figure 5(b), sensors S1, S4, and S9 have significantly high critical physiological-data to transmit. The power consumption ratio and probability of collisions 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 Figure 5(a).

Figure 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 collision probability associated with these three sensors.

Figures 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

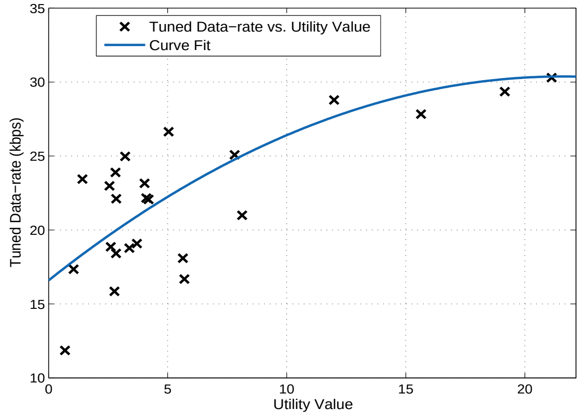


Fig 7. Data-rate vs Utility Value (Curve fitting)

utility function for body sensor devices. These plots also depict how much the parameters contribute to the utility function. We also plot the nature of change of the tuned data-rate with the increase of utility value, i.e the combined effect of Criticality Index, Collision Probability and Power Consumption Ratio, through curve-fitting process in Figure 7, through MATLAB curve fitting tool.

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, Collision Probability, Power Consumption Ratio, along with the minimum demands of the sensors. With these parameters we decide the relative priorities of the sensors involved in the WBAN. Evidently, this approach leads to a better tuning that specially take care the criticality of measured physiological data while tuning data-rate at a particular time instance, through increasing the data-rate for critical sensor nodes by 10% on an average. In future, we plan to consider selfish behavior of body sensor nodes and wish to expand this novel work by introducing the concept of dynamic bargaining power as a positive or negative reward function for each sensors.

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