Prioritized Payload Tuning Mechanism for Wireless Body Area Network-Based Healthcare Systems

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***Abstract*—This paper presents a priority-based MAC-frame payload tuning mechanism with reduced energy consumption for healthcare systems that use Wireless Body Area Networks (WBANs). A fundamental problem in WBANs is to prioritize the physiological sensors depending on several health and external criteria. The challenge is to design a dynamic decision making model that can optimize the energy consumption of each physiological sensor. To address this problem we employ the concept of Fuzzy Inference System (FIS) in order to calculate Criticality Index (CI), which signifies the severity or the priority of the physiological data sensed by each sensor. Considering the obtained CI value we proceed with designing a dynamic decision making model based on the concept of Markov Decision Process (MDP) in order to tune MAC-frame payload by optimizing the energy consumption of each sensor node. We achieve around 25% decrease in the overall energy consumption using our proposed mechanism.**

***Index Terms*—Wireless Body Area Network, Fuzzy Inference System, Markov Decision Process, Prioritized Payload Tuning.**

I. Introduction

A number of modern healthcare applications are egressing, among which eHealth oriented applications based on Wireless Body Area Networks (WBANs) are prominent. Priority-based health monitoring, and maximizing the life of each low-power physiological sensor through the reduction of overall energy consumption are the open areas of innovation. Therefore, health criticality measurement and priority-based dynamic decision making based on measured health criticality is the main objective of our proposed work.

A. Motivation

Health parameters such as body temperature, heart rate, pulse rate, blood pressure, and oxygen saturation in blood can be sensed using different physiological sensors. The values of these parameters depend not only on the health condition, but also on other external constraints such as the age, height, weight and the sex of a particular human being. It is not accurate if we use the concepts of crisp set to categorize health status into different groups. In crisp set theory, we can only interpret a particular health parameter as ‘low’,‘moderate’, and ‘high’ compared to its normal value. However, it is a challenge to quantify how much it is low, moderate or high from its expected measure. Therefore, it results into inefficient decision making in any application where this approach has been taken. This problem in traditional healthcare system motivates us to propose a fuzzy inferencing-based health criticality assessment approach followed by an efficient decision making model based on the concepts of Markov Decision Process (MDP).

B. Contribution

The specific contributions of this work are as follows:

- We quantify the severity of a physiological parameter through Criticality Index (CI).
- We envision a fuzzy approach to determine the severity of a particular physiological parameter.
- The proposed payload tuning mechanism is also efficient in terms of total energy consumption by the network.

II. Related Works

Though modern world is moving towards advanced healthcare systems using WBANs [1]–[4], there is inadequacy of work on efficient MAC-frame payload tuning mechanisms in this network technology. There exists some simulation-based works [3] and some analytical studies [4] to deal with throughput, delay, and power consumption of IEEE 802.15.4. Park et al. proposed a three dimensional Markov chain model for IEEE 802.15.4 and presented optimization techniques for optimizing different network parameters such as reliability, delay, and energy consumption in [5]. However, none of them considers the severity of health data and its effect on the overall network performance.

Lack of relevant works using fuzzy logic and Fuzzy Inference Systems (FIS) in healthcare systems are also noticed. Lau et al. proposed a fuzzy logic based hand-off algorithm that controls signal variation and dynamic adaptation of hysteresis level with the signal differences between two stations [6]. Similarly, in the domain of cellular network, a fuzzy logic based algorithm is proposed to make hand-off decisions in the

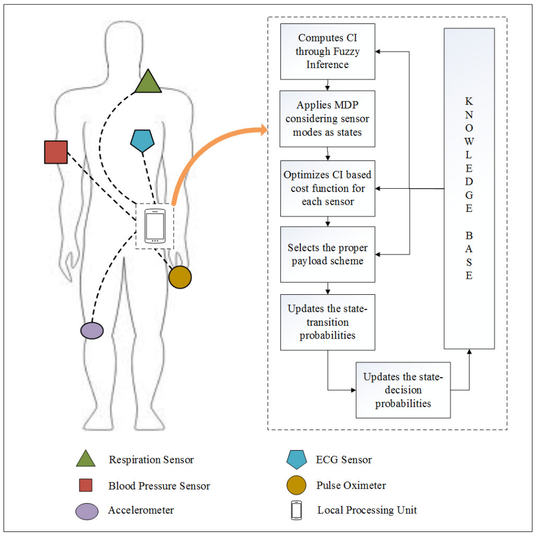


Fig. 1: LPU Functionalities

boundary between adjacent cells [7]. Qiu proposed congestion avoidance and control schemes based on fuzzy set theory [8]. Our literature survey does not reveal any work related to healthcare systems that employ fuzzy set theory concepts.

There are some relevant works on the use of MDP for addressing different network and healthcare problems. In [9], the authors proposed an MDP-based solution to address the problem of how the failed nodes are to be replaced, to obtain a profitable balance between maintenance cost and network performance. Bennett and Hauser [10] developed a general purpose computational/artificial intelligence framework to address a simulation environment for exploring various healthcare policies, and payment methodologies.

Synthesis: In our work, we use the concept of fuzzy inferencing to fuzzify health parameters and external constraints. We also use MDP as the decision making approach in such a manner that the system harnesses the benefits from both networking and medical perspectives.

III. Problem Scenario

In order to address the problem discussed in Section I, we define three fuzzy sets and a membership function to represent the grade of membership of a particular health parameter value to a particular fuzzy set. We also do the same for the external factors such as age, height, and weight that have significant influence on health parameters. We form several fuzzy rules depending on these fuzzy sets and membership functions to achieve a justified value of Criticality Index (CI) for each sensor. The advantage of using fuzzy sets is that all fuzzy rules are fired with some degree of membership. In other words, we get contributions from all treated criteria while appropriating the CI value for a particular sensor at a given instant of time.

Definition 1. *(Criticality Index) The Criticality Index ($\psi_{s,t}$) of the sth sensor is the measure of seriousness of the health parameter that is being measured by that physiological sensor at the time instant* t.

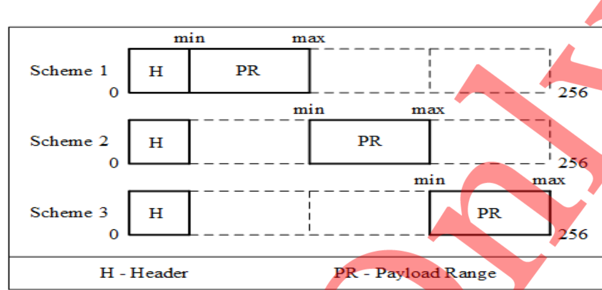


Fig. 2: Payload schemes

After defuzzifying we get a crisp value of CI that strictly ranges from 0 (low critical) to 1 (high critical). We use this $\psi_{s,t}$ value while modelling cost functions in the proposed MDP. The physiological sensors can take certain decisions from a pool of randomized decision based on different criteria that are explained thoroughly in Section IV. The problem is to select a particular decision regarding the operational modes of sensors and MAC-frame payload schemes in a particular state, considering probabilistic transitions within these states, and considering the associated cost of each possible decision in that state. We consider three payload schemes which are different from each other in terms of their minimum and maximum values. The IEEE 802.15.6 protocol allows maximum 256 Bytes (including header), as the maximum size of a MAC-frame [11]. We divide the total payload range (excluding the header) into three equal ranges, as illustrated in Figure 2. Each of the three payload schemes possesses different minimum and maximum values. We employ the theory of MDP to select appropriate payload scheme for a particular sensor, so that the sensor can use a payload size within the payload range (PR) of the selected scheme. All the necessary computations are done by the Local Processing Unit (LPU) associated with each WBAN or each human being, as illustrated in Figure 1.

IV. Mathematical Model

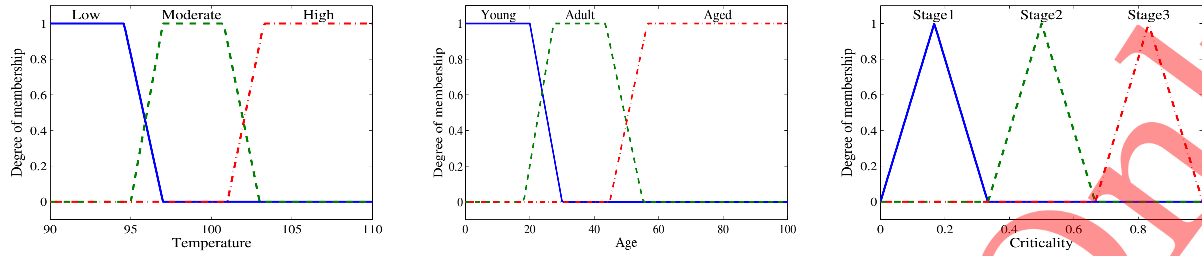
In this Section, we briefly discuss the concepts of fuzzy logic, FIS, and MDP and how they help us to address the problem stated in Section III.

A. Fuzzy Inference System

A fuzzy inference system consists of several fuzzy sets and fuzzy rules. First, we describe the fuzzy sets we consider in this inference system. In fuzzy set theory an object can be a member of more than one set. This kind of partial membership can be defined using a *membership function* for that particular set. A fuzzy set F is represented as a set of ordered pairs [12],

$$F = \{(x, \mu_F(x)) | x \in X\} \qquad (1)$$

where X denotes a collection of objects and x represents each object from this collection. $\mu_F(x)$ is the membership function or *grade of membership* [13] of an object x in a fuzzy set F. This membership function is a mapping of the collection of objects to a membership value set. The motivation behind the use of fuzzy logic is to avoid binary assessment



(a) Body Temperature (in Fahrenheit) (b) Age (in Years) (c) Criticality Index

Fig. 3: Fuzzy Sets and Membership Functions

of health parameters to get more appropriate view. Different fuzzy sets and membership functions are required to estimate the severity of each parameter related to human health. Human age also plays a crucial role to determine normal values of different physiological parameters [14]. Thus, along with the direct health parameters, we also consider human *age* as an influential criteria to judge the criticality of health data.

We envisage linguistic sets such as 'LOW', 'MODERATE', and 'HIGH' to categorize the severity of each health parameter and define the corresponding membership functions for them. In case of human age we acknowledge three sets such as 'YOUNG', 'ADULT', and 'AGED'. For example, Figure 3(a) represents the mapping between human body temperature and its degree of membership at different values. Similarly, Figure 3(b) represents the fuzzy logic behind the categorization of human age and Figure 3(c) represents the fuzzy logic behind the criticality of a particular health parameter. The fuzzy sets are represented through full lines, dashed lines and dashed dotted lines in these figures.

Linguistic variables are dependent on one another and these dependencies can be represented through conditional (if-then) statements or rules [12]. We employ more than one antecedent (inputs) and single consequent (output) approach, where the output is the defuzzified CI value of each sensor. We foresee different rules in order to capture the combined effect of health parameters and external constraints on criticality index. We store these rules in a rule-base where each rule is assigned a unique ID. The i^{th} rule is represented as R_i such that [15],

$$R_i = \begin{cases} x_1 = \alpha_{1,i}, x_2 = \alpha_{2,i}, ..., x_n = \alpha_{n,i} \\ \rightarrow y = \beta_i \end{cases} \tag{2}$$

where, $x_1, x_2, ..., x_n$ are the antecedent or input variables and $\alpha_1, \alpha_2, ..., \alpha_n$ are the fuzzy sets. β_i is the fuzzy set of consequent or output for i^{th} rule.

We use the Mamdani model [16], the most commonly used fuzzy inference technique on these fuzzy rules. In a nutshell, this technique fuzzifies the input variables, evaluates the rules, aggregates the rule outputs and defuzzifies to get a final crisp value of CI for each physiological sensor. For example, we select a rule from the rule-base, say rule R_i. If we use m inputs or antecedents, then the fuzzification process produce m membership values such as $\mu_{A_1,t}(x_1)$, $\mu_{A_2,t}(x_2)$, and so on upto $\mu_{A_m,t}(x_m)$ respectively for criteria A_1, A_2, upto A_m at a time instant t. Mamdani model evaluates each rule through its firing strength. The firing strength of R_i at time instant t ($\mu_{R_i,t}$) is the minimum membership value of the associated antecedents in the rule. Mathematically,

$$\mu_{R_i,t}(x_1, ..., x_m) = min\Big[\mu_{A_1,t}(x_1), \mu_{A_2,t}(x_2), ..., \mu_{A_m,t}(x_m)\Big] \tag{3}$$

If we consider n such rules, then the aggregation of these n rules in the Mamdani model takes place through the max operator. The output can be represented as,

$$\mu_{R,t}(c) = max\Big[\mu_{R_1,t}(x_1, ..., x_m), \mu_{R_2,t}(x_1, ..., x_m), ..., \mu_{R_n,t}(x_1, ..., x_m)\Big] \tag{4}$$

The last step of the fuzzy inference process is defuzzification, which converts the fuzzy aggregated output into a crisp number, which denotes the Criticality Index (ψ) in this work. Most popular defuzzification technique is the *centroid* technique. Mathematically, the Criticality Index for the s^{th} sensor at the time instant t can be represented as,

$$\psi_{s,t} = \frac{\int_0^1 \mu_{R,t}(c).c \, \mathrm{d}c}{\int_0^1 \mu_{R,t}(c) \, \mathrm{d}c} \tag{5}$$

B. *Markov Decision Process*

From the proposed FIS we get a defuzzified value of ψ for a particular sensor node. We introduce the concept of different operational states such as 'REST', 'ACTIVE', and 'HIGHLY ACTIVE' for each sensor and different possible decisions in those states. Based on certain criteria such as the state transition probabilities, the probability of taking a particular decision at a particular state, and the associated cost with probable decisions, the proposed MDP optimizes the cost and finalizes the decisions for each of these states. A state can opt for more than one decision, but not at the same time. The decisions considered in this work are summarized in Table I. Before proceeding further we need to discuss some basic properties of Markov chain in order to focus on our problem. In our paper, we formulate a Markov chain as a sequence of stochastic operational states $S_1, S_2, S_3, ...$ and so on, satisfying the Markov property. Mathematically, $P(S_{n+1} = x | S_1 =$

$x_1, S_2 = x_2, ..., S_n = x_n,) = P(S_{n+1} = x | S_n = x_n)$, for $n = 0, 1, ...,$ and so on [17].

We also describe *m-step transition probabilities*, as follows [17]: $P_{ij}^m = P(S_{n+m} = j | S_n = i)$.

We need to understand another property of Markov chain in order to focus on our problem. While calculating the m-step transition probabilities, if m is large enough, then there exists a limiting probability that the system will be in state j after a large number of transitions, and this probability is independent of the initial state. It is known as the *steady-state probability*. For any irreducible ergodic Markov chain, $\lim_{m\to\infty} P_{ij}^m$ exists, and is independent of i.

$$\lim_{m\to\infty} P_{ij}^m = \eta_j > 0, \tag{6}$$

where the steady-state probability of state j (η_j) uniquely satisfies the following steady-state equations [18]:

$$\eta_j = \sum_{i=0}^{m} \eta_i P_{ij} \tag{7}$$

for j=1, 2,..., m, and

$$\sum_{j=0}^{m} \eta_j = 1. \tag{8}$$

We now explain the application of this property in our problem.

TABLE I: Set of decisions

Decision	Action	Next State
1		Rest
2	Enable payload scheme 1	Active
3		Highly Active
4		Rest
5	Enable payload scheme 2	Active
6		Highly Active
7		Rest
8	Enable payload scheme 3	Active
9		Highly Active

The model of the MDP considered in this paper is summarized as follows.

1) The state i of a discrete time Markov chain is observed after each transition (i = 1, 2,..., N).
2) After each observation, a decision k is chosen from a set of K possible decisions (k = 1, 2,..., K). We define the corresponding *State-Decision Probability Matrix* below.

Definition 2. *(State-Decision Probability Matrix) $A_{s,t,ik}$ is the State-Decision Probability Matrix of the* sth *sensor with* N *states and* K *decisions and the element a_{ik} is the probability of opting decision* k *at state* i *at time* t.

$$A_{s,t,ik} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1K} \\ a_{21} & a_{22} & \cdots & a_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NK} \end{bmatrix} \tag{9}$$

where each row sums to 1 and $0 \leq a_{ik} \leq 1$.

3) If decision k is made in state i for the s^{th} sensor at time instant t, an immediate cost is incurred by that decision, that is expressed by the following definition of State-Decision Cost matrix.

Definition 3. *(State-Decision Cost Matrix) $\Delta_{s,t,ik}$ is the State-Decision Cost Matrix of* sth *sensor with* N *states and* K *decisions and the element $\Delta_{ik}(\xi,\psi)$ is the immediate cost incurred by decision* k *made at state* i *at time instant* t.

$$\Delta_{s,t,ik} = \begin{bmatrix} \Delta_{11}(\xi,\psi) & \Delta_{12}(\xi,\psi) & \cdots & \Delta_{1K}(\xi,\psi) \\ \Delta_{21}(\xi,\psi) & \Delta_{22}(\xi,\psi) & \cdots & \Delta_{2K}(\xi,\psi) \\ \vdots & \vdots & \ddots & \vdots \\ \Delta_{N1}(\xi,\psi) & \Delta_{N2}(\xi,\psi) & \cdots & \Delta_{NK}(\xi,\psi) \end{bmatrix} \tag{10}$$

where $\Delta_{ik}(\xi,\psi)$ is a function that takes ξ and the defuzzified ψ value as parameters and calculate the cost for that particular state-decision pair. ξ is the variable that represents the ratio of total energy dissipation due to payload scheme change (ξ_p) and state change (ξ_s) to the residual energy of s^{th} sensor at time instant *t* (ξ_t). Mathematically ξ can be represented as below.

$$\xi = \frac{\xi_p + \xi_s}{\xi_t} \tag{11}$$

4) We propose a learning-based State Transition Probability Matrix to represent all the transition probabilities for s^{th} sensor at time instant *t*.

Definition 4. *(State Transition Probability Matrix) $P_{s,t,ij}$ is the Transition Probability Matrix of the* sth *sensor node for* N *states and the element P_{ij} is the probability of transition from state* i *to state* j *at time instant* t.

$$P_{s,t,ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1N} \\ P_{21} & P_{22} & \cdots & P_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ P_{N1} & P_{N2} & \cdots & P_{NN} \end{bmatrix} \tag{12}$$

where each row sums to 1 and $0 \leq P_{ik} \leq 1$.

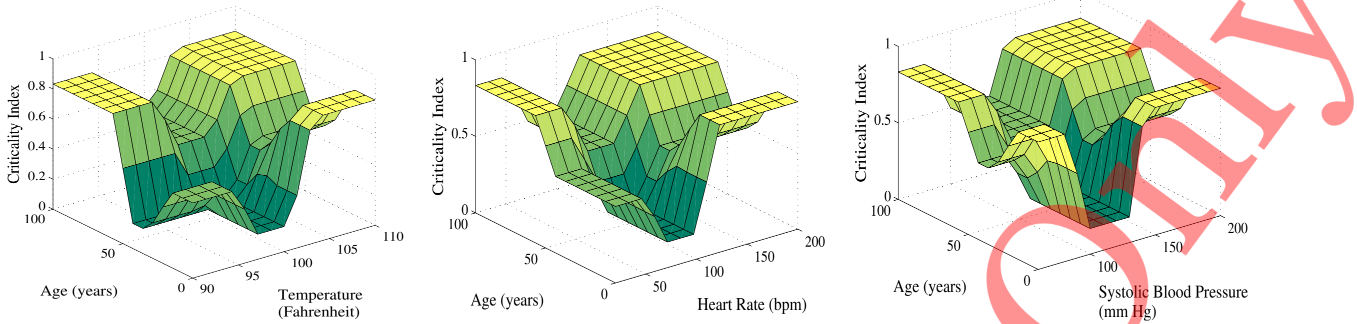
5) The objective of this work is to find an optimal policy by minimizing the cost associated with the decisions.

By allowing randomizing policies, so that $A_{s,t,ik}$ are continuous variables instead of integer ones, it is now possible to formulate a linear programming model for finding an optimal policy. For each *i* = 1, 2,..., n, and *k* = 1, 2,..., k, let there be a steady-state unconditional probability that the system is in state *i* and decision *k* is made. It is represented as, $\delta_{s,t,ik} = P(state = i \text{ and } decision = k)$ for *s*-th sensor at time instant *t*. Each $\delta_{s,t,ik}$ is closely related to the corresponding $A_{s,t,ik}$. From the conditional probability rules,

$$\delta_{s,t,ik} = \eta_{s,t,i}\, A_{s,t,ik} \tag{13}$$

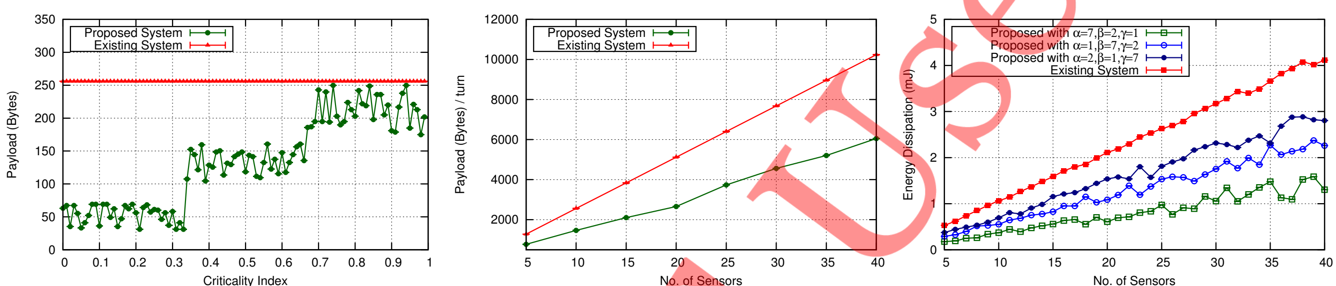
where $\eta_{s,t,i}$ is the steady-state probability that the s^{th} sensor is in state *i* at time instant *t*. From the properties of steady-state probability, we have [19]:

$$\eta_{s,t,i} = \sum_{k=1}^{K} \delta_{s,t,ik} \tag{14}$$



(a) Influence of Body Temperature and Age (b) Influence of Heart Rate and Age (c) Influence of Blood Pressure and Age

Fig. 4: Inputs vs Criticality Index



(a) Payload vs Criticality Index (b) Payload/turn vs No. of sensors (c) Energy dissipation vs No. of sensors

Fig. 5: QoS Evaluation

Therefore, from Equations (13) and (14), we have,

$$A_{s,t,ik} = \frac{\delta_{s,t,ik}}{\sum_{k=1}^{K} \delta_{s,t,ik}} \tag{15}$$

There are some constraints on $\delta_{s,t,ik}$. They are as follows [17].

1)
$$\sum_{i=1}^{N} \eta_{s,t,i} = 1 \tag{16}$$

From Equations (14) and (16) we have:

$$\sum_{i=1}^{N} \sum_{k=1}^{K} \delta_{s,t,ik} = 1 \tag{17}$$

2) From the results of steady-state probabilities stated in Equation (7), we conclude:

$$\sum_{k=1}^{K} \delta_{s,t,jk} = \sum_{i=1}^{N} \sum_{k=1}^{K} \delta_{s,t,ik}\ P_{s,t,ij}(k), \text{ for } j = 1, 2, ..., N. \tag{18}$$

3) $\delta_{s,t,ik} \geq 0$, for i = 1, 2,..., N, and k = 1, 2,..., K.

We formulate the total cost incurred by a particular sensor node during decision making at time instant t and we follow the procedure for each sensor. The expected average cost per unit time is given below [17].

$$\begin{aligned} E(s,t,\Delta) &= \sum_{i=1}^{N} \sum_{k=1}^{K} \eta_{s,t,i}\ \Delta_{s,t,ik}\ A_{s,t,ik} \\ &= \sum_{i=1}^{N} \sum_{k=1}^{K} \Delta_{s,t,ik}\ \delta_{s,t,ik} \end{aligned} \tag{19}$$

Therefore, the linear programming model is to solve $\delta_{s,t,ik}$ so as to minimize

$$Z = \sum_{i=1}^{N} \sum_{k=1}^{K} \Delta_{s,t,ik}\ \delta_{s,t,ik} \tag{20}$$

subject to the constraints,

1) $\sum_{i=1}^{N} \sum_{k=1}^{K} \delta_{s,t,ik} = 1$,
2) $\sum_{k=1}^{K} \delta_{s,t,jk} - \sum_{i=1}^{N} \sum_{k=1}^{K} \delta_{s,t,ik}\ P_{s,t,ij}(k) = 0$, for j = 1, 2,..., N.
3) $\delta_{s,t,ik} \geq 0$, for i = 1, 2,..., N, and k = 1, 2,..., K.

This linear programming model is solvable by several existing methods. After getting the $\delta_{s,t,ik}$ values, we also compute the $A_{s,t,ik}$ values using Equation (15). These $A_{s,t,ik}$ values decide the optimal and cost-effective set of actions that we should adopt in a particular state of s^{th} sensor at time instant t.

V. Analytical Result

In this Section, we evaluate the influence of physiological parameters along with an external criteria on health. We also provide comparative results to prove energy efficiency of the proposed solution.

A. Analysis of proposed FIS

We consider three health parameters such as body temperature, heart rate, and systolic blood pressure along with the age as an external criteria in our experiment done through Fuzzy Toolbox in MATLAB. For example, the fuzzy sets and membership functions for body temperature and age is illustrated in Figure 3 in Section IV. Figure 4(a) illustrates the effect of body temperature on health criticality for different ages. The Z-axis represents the severity of health in terms of Criticality Index. Analyzing the graph, we can easily verify that Criticality Index gets maximum value (approximately 0.8) mostly when aged persons are suffering from high temperature. Similarly, high temperature for children is equally critical. Figure 4(b) depicts the effect of heart rate with age as same external criteria. Similarly, Figure 4(c) illustrates the influence of systolic blood pressure on Criticality Index.

B. Analysis of proposed MDP and final result

This experiment involves minimum 5 and maximum 40 physiological sensors in a WBAN environmen. We consider the transmission energy dissipation rate for each sensor as 50 nJ/bit. We compare the proposed solution with existing system that constantly uses a maximum payload size of 256 Bytes as defined in IEEE 802.15.6 protocol for WBANs.

Figure 5(a) illustrates the effect of health criticality on priority-based MAC-frame payload tuning. Existing system uses a constant amount of payload irrespective of the health condition sensed by a particular physiological sensor. However, using a high payload for the sensors which are in less critical condition, leads to unnecessary energy consumption. Whereas, the proposed solution allows the system to tune the MAC-frame payload into three different ranges and it is evident from this figure that the decision depends on several factors including the Criticality Index. Figure 5(b) compares the total amount of payload used by sensors in the proposed solution with the existing system. We vary the number of physiological sensors from 5 to 40 and consider different distributions of operational modes for each case. We plot the average payload usage in each turn and through comparison we show that it is much less than the average payload usage in case of existing system.

We also compare the energy dissipation amount (per frame transmission per sensor) of the existing system and the proposed solution. Figure 5(c) depicts this comparison where α, β, and γ are the ratio of sensors that selects payload scheme 1, 2, and 3 respectively at a time instant. It is evident from this figure that the proposed solution of priority-based MAC-frame payload tuning is also energy efficient with respect to the existing system. Through analysis we conclude that it consumes almost 25% less energy than the existing system.

VI. Conclusion

In this paper, we presented an efficient approach for MAC-frame payload tuning among the physiological sensors associated with a WBAN-based healthcare system. The proposed solution confronts two major problem in WBAN related study such as formulation of Criticality Index of each sensor to prioritize them and a proper decision making approach for payload tuning based on the prioritization. We compared with existing system and verified that energy efficiency is a considerable achievement of this proposed solution. In the future, we plan to propose a QoS aware approach where sensors that constantly suffer from low QoS due to low priority, can be awarded adaptive rewards through some trade-off mechanism to ensure the benefit of whole network.

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