CARE: Criticality-Aware Data Transmission in CPS-based Healthcare Systems

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***Abstract*—In this paper, we propose a scheme, *criticality-aware data transmission* (*CARE*), in CPS-based healthcare systems, for increasing the processing rate of the sensed physiological parameters' values of a patient. The criticality of a patient may vary at any instant of time, and thus, continuous monitoring and quick processing of the physiological parameter value of a patient is essential. Therefore, in order to reduce the latency of data processing of a critical patient, we consider a fog computing based architecture to address the problem. Based on the criticality value of physiological parameters, a Local Processing Unit (LPU) transmits the sensor data either to the fog aggregation node or cloud. We use a cooperative game theory-based *Nash* bargaining approach, where the LPUs bargain among themselves to decide whether the sensor data need to be transmitted to cloud or fog aggregation node. Based on the criticality index and the weight factor assigned to the LPU participating in the bargaining process, the utility of each LPU is computed. Analytical results show that the utility increases with the increase in the criticality index of any patient. Considering the total number of WBANs 5, 10, and 15, the average utility varies between 75-80%. Moreover, the data dissemination delay and power consumption are reduced by 23.39% and 31.089%, respectively, in the presence of fog node.**

Keywords*—Cyber Physical Systems, WBAN, Criticality index, Nash Bargaining, Fog aggregation node, Cooperative game.

I. Introduction

The rapid development in Cyber Physical Systems (CPS) [1] requires efficient connectivity between the physical and cyber world. The increasing number of physical devices results in significant use of cloud platform for storing and processing of data. The cloud computing systems use data-centric network (DCN), which acts as a monopolized unit for computation and storage. Currently, the processing of the huge volume and variety of data produced from billions of physical devices is quite challenging. However, the fog computing adapts a decentralized architecture, which has limited computing capabilities along with short-term storage facilities. Fog computing [2] provides a platform, where heterogeneous devices are able to communicate, cooperate, and process tasks among themselves without the help of a third party. Additionally, fog computing allows the analysis of time-sensitive data at the network edge and process it within a very short time duration. Therefore, fog computing reduces latency and consumes less bandwidth.

CPS plays an important role for ubiquitous patients' health monitoring. [3]. In a CPS-based Wireless Body Area Network (WBAN), different physiological sensors are typically placed on the patient's body to keep continuous track of the physiological parameters of a patient. In the existing literature, the authors addressed different issues of WBAN, including data-rate tuning [4], data distribution cost minimization [5], and cost-effective resource allocation [6]. However, the time-sensitivity of critical data processing is not focused significantly. The criticality of a patient may vary at any time instant. With the increasing criticality of a patient, the processing speed of the physiological parameters' values must also be increased for further immediate decision making. The delay in processing of physiological data of a patient may result in degradation of a patient's health condition. Therefore, we design a scheme to transmit physiological data based on the criticality of the patient, so that the data are further processed. We use a cooperative game theory-based approach, where LPUs located on patients' body bargain among themselves to decide whether the physiological data need to be transmitted to the fog aggregation node or to the cloud directly.

A. Motivation

The delay in transmission and processing of physiological parameters may result in increase of a patient's health criticality. Thus, the time-sensitiveness of physiological data transmission is an essential issue, which needs to be taken into account for a WBAN-enabled hospital. Therefore, we motivated to design a novel scheme for prioritized data processing among several patients based on their health-criticality value. In an IoT-enabled WBAN scenario, the physiological data are transmitted to the fog nodes or to the cloud-end directly. In our proposed scheme, CARE, we use a cooperative game theoretic Nash bargaining approach. Bargaining takes place among the LPUs of different patients in order to provide an equal priority to each patient for physiological data transmission based on their criticality values. We consider the scenario in which multiple patients are present in a hospital, where CARE is able to decide whether the sensed physiological data of patients are needed to be transmitted to the cloud or fog.

B. Contribution

In this work, we focus on the time-sensitiveness of physiological sensor data of a patient's body. The specific *contributions* of this work are as follows:

1) We propose a novel scheme, CARE, which decides whether to transmit the physiological sensor data to the fog aggregation node or the cloud, based on the patient's criticality.
2) We derive an index, which measures the health criticality of a patient, based upon which the physiological parameters are transmitted to the cloud or the fog. Further, we model the problem as a *Nash Bargaining* process, where the LPUs act as players and bargain among themselves to transmit the data to a cloud or fog node.
3) The proposed scheme, CARE, is analyzed through simulation and analytical studies.

The rest of the paper is organized as follows. Section II describes the related research works done in Wireless Body Area Networks (WBAN). The system architecture of CARE is described in Section III. The proposed architecture, CARE, is evaluated in Section IV and performance analysis is done in SectionV. Finally, the work concludes in Section VI, while citing directions for future work.

II. Related Work

In recent years, research on WBANs is explored exhaustively and the authors in the existing literature [4]–[7] addressed several issues in WBANs. Ivanov *et al.* [7] proposed an architecture for virtual group formation of nurses, doctors, and patients to remotely analyze WBAN data. Group formation and modifications are performed using high-level policies. The authors defined a new metric, *Quality of Health Monitoring*, using which doctors provide feedback about the quality of the received physiological parameters of the patient. In real-time data streaming of WBANs, Quality of Service (QoS) plays an important role. Thus, Misra *et al.* [4] applied a cooperative game theoretic approach for priority based data-rate tuning among the sensor nodes to improve the QoS. Moulik *et al.* [6] introduced the concept of Multi-stage Nash Bargaining for allocating resources in WBAN. The authors cost-effectively map WBANs to the Cloud Service Providers (CSP). Moosavi and Bui [8] focused on the physical layer security aspects. The authors proposed a game-theoretic Nash network topology in order to improve the security in data transmission.

Fog computing provides the platform to analyze the time-sensitive data at the network edge. Vaquero *et al.* [2] presented a complete definition of fog and the various research challenges related to fog. Further, Misra *et al.* [9] proposed the architecture of fog computing. In this work, the authors mathematically derive power consumption, service latency, and CO_2 released to the environment in the case of renewable and non-renewable energy resources. The fog layer offers gateways to provide various techniques and services at the edge network. Gia *et al.* [10] designed a healthcare monitoring system for ECG feature extraction using fog computing. In this system, the ECG signals are examined by extracting the various features.

Synthesis: In the existing literature, the researchers addressed different problems in WBAN, including data rate tuning, mapping of WBANs with CSPs, quality of physiological data, and security. On the other hand, fog computing became an emerging topic of research. Different authors in the existing literature explored fog computing, and thereafter, provide solution to strengthen the concept theoretically and practically. However, none of the existing literature to our knowledge discussed about the implementation of fog computing in WBAN, considering the criticality based data delivery for processing. Therefore, we design a scheme to transmit data based upon the value of the criticality index of the patient. The criticality of any patient varies at any time instant. Therefore, any delay in the delivery of the physiological parameters may worsen the patient's condition.

III. Problem Description

A. Problem Scenario

We consider a WBAN provisioned hospital scenario, where multiple heterogeneous on-body sensor nodes are placed on the bodies of patients. Each of these sensor nodes transmits the values of physiological parameters of a patient to the LPU. The health criticality of any patient is influenced by the deviation of the sensors' values from their normal values. Therefore, in such a situation, constant monitoring of the patient is important. Additionally, the physiological data of a patient, which are required to be transmitted by the LPU, are time-sensitive. Consequently, for a critical patient, the quick processing of physiological sensor data is required. Based on the patient's criticality, the LPU transmits physiological data either to the fog node or the cloud, as shown in Fig. 1.

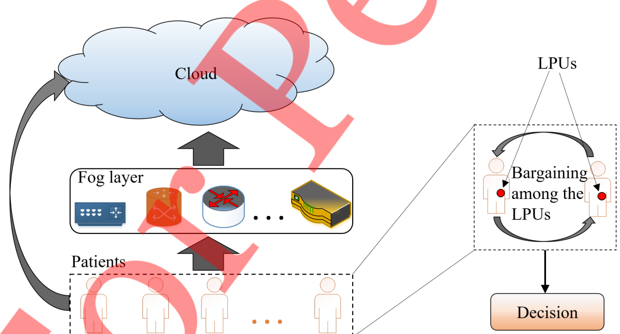

Fig. 1: CARE – The System Architecture

$$\mathbb{CI}_{W_i} = \frac{1}{\xi_{W_i}} \left(\sum_{p=1}^{x} \frac{|\mathcal{D}^p_{min} - S^p_{min}|}{S^p} + \sum_{q=1}^{y} \frac{|\mathcal{D}^q_{max} - S^q_{min}|}{S^q} + \sum_{r=1}^{z} \frac{(\mathbb{O}^r_c - S^r_{min})}{S^r} \right) \quad (3)$$

B. Problem Formulation

Let $\mathbb{W} = \{W_1, W_2, W_3, \cdots, W_d\}$ be the set of WBANs present in the system, where $1 \leq i \leq d$. We consider $\xi_{W_i} = \{X_1, X_2, \cdots, X_n\}$ to be the set of sensors attached to the body of W_i^{th} WBAN, where $X_j \in \xi_{W_i}$ and $1 \leq j \leq n$. Each sensor has a normal value, $\mathbb{N}$, such that $\mathbb{N}_{min} \leq \mathbb{N} \leq \mathbb{N}_{max}$. The deviation of the sensor's value of any patient beyond $\mathbb{N}_{min}$ and $\mathbb{N}_{max}$ is considered to be critical. The value of the physiological sensor less than $\mathbb{N}_{min}$ is denoted by $\mathcal{D}_{min}$ and the physiological sensor value more than $\mathbb{N}_{max}$ is denoted by $\mathcal{D}_{max}$. S_{min} and S_{max} denote the minimum and maximum possible value of a sensor, such that $S_{min} \leq \mathbb{N} \leq S_{max}$. Mathematically,

$$\mathcal{D}_{min} = \mathbb{N}_{min} - \mathbb{O}_c, \quad \text{and} \quad \mathcal{D}_{max} = \mathbb{O}_c - \mathbb{N}_{max} \tag{1}$$

where $\mathbb{O}_c$ is the current observed value of the sensor. Let x, y, and z denote the set of physiological sensors, which attain $\mathbb{O}_c < \mathbb{N}_{min}$, $\mathbb{O}_c > \mathbb{N}_{max}$, and $\mathbb{N}_{min} \leq \mathbb{O}_c \leq \mathbb{N}_{max}$ respectively. Therefore,

$$x + y + z = \xi_{W_i} \tag{2}$$

We define the criticality index ($\mathbb{CI}_{W_i}$) of the W_i^{th} patient mathematically in Equation (3), where $S = S_{max} - S_{min}$.

IV. Solution Approach

We provide a solution of the proposed problem using a cooperative game-theoretic *Nash bargaining* approach. We focus on the health criticality of the patients in order to transmit the sensed physiological data from a patient's body to the fog aggregation node or cloud.

A. Game formulation

We formulate the problem of selection between fog and cloud for physiological data processing of a patient as a cooperative game. Each WBAN's LPU acts as a player and cooperatively bargains with other LPUs to attain an optimal solution for choosing cloud or fog node. Through bargaining, the players mutually agree to transmit the selected WBAN's physiological parameters' value to the fog aggregation node or cloud, as illustrated in Fig. 1. Based on the health criticality index of any patient, the utility of the corresponding LPU is computed at that time instant. Each LPU bargains with others, depending on their individual utility values. Therefore, we map this problem scenario with the *bargaining process* [11]. Depending upon the bargaining outcome, a LPU transmits the physiological parameters of the corresponding patient to the cloud or fog node.

We consider $\mathbb{L} = \{\mathcal{L}_1, \mathcal{L}_2, \mathcal{L}_3, \cdots, \mathcal{L}_k\}$ to be the set of LPUs. Each LPU, $\mathcal{L}_i$ $(1 \leq i \leq k)$ is associated with a WBAN, W_j $(1 \leq j \leq d)$ belonging to the set $\mathbb{W}$ present in the system. Let m LPUs participate in the bargaining process. We use a parameter as weight factor, γ, to provide certain weightage to the LPUs participating in the bargaining process. The weight factor, γ varies in the range $0 \leq \gamma \leq 1$. However, each participating LPU possesses different weights based on the criticality of the patient. For example, a critical patient, with high value of criticality index has greater weight compared to a patient with low criticality index. Therefore, $\mathcal{L}_x^t = \gamma_x^t L_x^t$. The utility function of the x^{th} LPU at any time instant t is denoted by $U_x(\mathcal{L}_x^t)$, where $x = 1, 2, \cdots, m$. We consider the m participating LPUs in the bargaining process as a closed set, which is denoted by Ψ. Therefore, the set of feasible utilities is mathematically represented as:

$$\Psi = \{(U_1(\mathcal{L}_1), U_1(\mathcal{L}_2), \cdots, U_1(\mathcal{L}_m)) | \mathbb{L} = (\mathcal{L}_1, \mathcal{L}_2, \cdots, \mathcal{L}_k) \in \mathbb{K}^c\} \tag{4}$$

where $\mathbb{K}^c$ is the space over which the players bargain to reach the outcome.

Each WBAN's LPU has a set of physiological parameters to transmit to the cloud or fog aggregation node. Based on the health criticality of the patient, a weight factor is associated with each participating LPU. Below a certain value of weight, γ_i^{min}, the i^{th} LPU, $\mathcal{L}_i$ does not cooperate in the game. This point is the *disagreement point* for the LPU participating in the bargaining process. Therefore, the set of disagreement points is mathematically represented as:

$$\mathbb{D} = \{D_{(min,1)}, D_{(min,2)}, D_{(min,3)}, \cdots, D_{(min,m)}\} \in \mathbb{K}^c \tag{5}$$

where $D_{(min,1)}$ denotes the disagreement point of $\mathcal{L}_1^{th}$ LPU corresponding to WBAN, W_1, with minimum weight, γ_1^{min}. $D_{(min,1)} = U_1(d_1)$, where d_1 is the point with minimum utility of $\mathcal{L}_1^{th}$ LPU.

Therefore, the *bargaining problem* is defined as $(\Psi, \mathbb{D})$, where $\Psi \subset \mathbb{K}^c$ and $\mathbb{D} \in \Psi$, such that it follows Theorem 1.

The utility of the x^{th} LPU, $\mathcal{L}_x$, at the present time instant $(t+1)$ is mathematically represented as :

$$U_x(\mathcal{L}_x^{t+1}) = \frac{\mathbb{CI}_{W_x}}{\tan^{-1}\left(e^{(\gamma_x^{t+1} L_x^{t+1}) - (\gamma_x^{min,t+1} D_{(min,x)}^{t+1})}\right)} \tag{6}$$

where $L_x^{t+1} \geq D_{(min,x)}^{t+1}$.

Theorem 1. *The joint utility set, Ψ, is a non-empty convex set.*

Proof: A set S in $\mathbb{K}^c$ is said to be convex [12], if a set of points $(y_1, y_2) \in \mathbb{K}^c$ and $\lambda \in (0,1)$, then $f(\lambda y_1 + (1-\lambda) y_2) \leq \lambda f(y_1) + (1-\lambda) f(y_2)$. Let Ψ_a and Ψ_b be two utility points in the joint utility set, Ψ, which are represented as:

$$\Psi_a = \{(U_1(\gamma_1 a_1), U_2(\gamma_2 a_2), U_3(\gamma_3 a_3), \cdots, U_m(\gamma_m a_m))\} \tag{7}$$

$$\Psi_b = \{(U_1(\gamma_1 b_1), U_2(\gamma_2 b_2), U_3(\gamma_3 b_3), \cdots, U_m(\gamma_m b_m))\} \tag{8}$$

The set Ψ is convex if,

$$U_x(\lambda\gamma_x a_x + (1-\lambda)\gamma_x b_x) \leq \lambda U_x(\gamma_x a_x) + (1-\lambda) U_x(\gamma_x b_x) \in \Psi \tag{9}$$

Therefore, the utility functions are represented as:

$$U_x(a_x^{t+1}) = \frac{\mathbb{CI}_{W_x}}{\tan^{-1}\left(e^{\gamma_x^{t+1} a_x^{t+1} - \gamma_x^{min,t+1} a_{min,x}^{t+1}}\right)} \tag{10}$$

$$U_x(b_x^{t+1}) = \frac{\mathbb{CI}_{W_x}}{\tan^{-1}\left(e^{\gamma_x^{t+1} b_x^{t+1} - \gamma_x^{min,t+1} b_{min,x}^{t+1}}\right)} \tag{11}$$

The first-order derivative of Equations (10) and (11) w.r.t. a_x and b_x are mathematically represented in Equations (12) and (13). Therefore,

$$\gamma_x^{t+1}(a_x^{t+1} - b_x^{t+1})\left(\nabla U_x(\gamma_x^{t+1} a_x^{t+1}) - \nabla U_x(\gamma_x^{t+1} b_x^{t+1})\right) \geq 0 \tag{14}$$

From Equations (12) and (13), we observe that the utility functions are differentiable on $\mathbb{K}^c$. Thus, from Equation (14), we conclude that Ψ is a non-empty convex set. ∎

Among m selected LPUs, the pair $(\Psi, \mathbb{D})$ defines the bargaining process. The point $(\gamma_1 L_1, \gamma_2 L_2, \cdots, \gamma_m L_m)$ is said to be the *Pareto Optimal Point*, where no other better allocation exists $(\{\gamma'_x L'_x \in \Psi | \gamma'_x L'_x > (\Psi, \mathbb{D}) \rightarrow \mathbb{K}^c\})$ in the bargaining problem.

The solution to the bargaining problem $F : (\Psi, \mathbb{D}) \rightarrow \mathbb{K}^c$ is mathematically expressed as:

$$\begin{aligned} F(U_1(\mathcal{L}_1), U_2(\mathcal{L}_2)) &= (U_1(\mathcal{L}_1) - D_{(min,1)}) \\ (U_2(\mathcal{L}_2) - D_{(min,2)}), &\quad \forall (U_1(\mathcal{L}_1), U_2(\mathcal{L}_2)) \in \Psi \end{aligned} \tag{15}$$

The bargaining outcome must satisfy the following four axioms [13]:

1) Pareto Efficiency
2) Symmetry
3) Invariant to affine transformations
4) Independence of irrelevant alternatives

Axiom 1. *The bargaining solution $F = (\Psi, \mathbb{D})$ is Pareto efficient.*

Justification: Suppose, there exist a point $((\gamma'_1 L'_1, \gamma'_2 L'_2) \in \Psi)$, so that $\gamma'_1 L'_1 > \gamma_1 L_1$ and $\gamma'_2 L'_2 > \gamma_2 L_2$. Moreover, $\gamma_x L_x > F_x(\Psi, \mathbb{D})$ for some x. Additionally, each LPU participating in the bargaining process must select a Pareto-efficient outcome where no LPU is preferred over the other participating LPUs.

Axiom 2. *The bargaining solution $F = (\Psi, \mathbb{D})$ is symmetrical in nature.*

Justification: Let us consider $((\gamma'_1 L'_1, \gamma'_2 L'_2) \in \Psi)$ maximize F over Ψ, if and only if $((\gamma'_2 L'_2, \gamma'_1 L'_1) \in \Psi)$ and $D_{(min,1)} = D_{(min,2)}$. Therefore, $F_1(\Psi, \mathbb{D}) = F_2(\Psi, \mathbb{D})$, such that the bargaining solution would not differentiate among the players.

Axiom 3. *The bargaining solution $F = (\Psi, \mathbb{D})$ is invariant to affine transformation.*

Justification: Suppose $(\Psi', \mathbb{D}')$ is the linear transformed form of $(\Psi, \mathbb{D})$ considering $\Psi'_x = \alpha_x \Psi_x + \beta_x$ and $\mathbb{D}'_x = \alpha_x \mathbb{D}_x + \beta_x$, where $\alpha_x > 0$. Mathematically,

$$F_x(\Psi', \mathbb{D}') = \alpha_x F_x(\Psi, \mathbb{D}) + \beta_x \tag{16}$$

Therefore, the outcome of the bargaining is invariant to linear transformation.

Axiom 4. *The bargaining solution $F = (\Psi, \mathbb{D})$ is independent of irrelevant alternatives.*

Justification: Let us consider two bargaining problem scenarios $(\Psi, \mathbb{D})$ and $(\Psi', \mathbb{D})$, such that $\Psi' \subseteq \Psi$. If $F(\Psi, \mathbb{D}) \in \Psi'$, then $F(\Psi', \mathbb{D}) = F(\Psi, \mathbb{D})$. We conclude that if the bargaining is performed in the utility region Ψ, it results in the solution $F(\Psi, \mathbb{D})$, such that Ψ' lies in Ψ. Therefore, hypothetical bargaining is performed in the utility region Ψ', which will also lead to the same outcome. The m LPUs, who participate in the bargaining process, bargain among them depending upon the criticality index of the patient. The LPUs negotiate among themselves to reach the bargaining outcome. Therefore, depending upon the outcome achieved, the LPU transmits data either to the fog aggregation node or cloud.

Theorem 2. *There exists a unique solution for the criticality-based data transmission among the LPU's participating in the bargaining process, satisfying the four axioms, and this solution is the pair of utilities $(\gamma_1^* L_1^*, \gamma_2^* L_2^*)$ that solves the following optimization problem.*

$$\underset{(\gamma_1 L_1, \gamma_2 L_2)}{argmax} (U_1(\mathcal{L}_1) - D_{(min,1)})(U_2(\mathcal{L}_2) - D_{(min,2)}) \tag{17}$$

such that $(\gamma_1 L_1, \gamma_2 L_2) \in \Psi$ *and* $(\gamma_1 L_1, \gamma_2 L_2) \geq (D_{(min,1)}, D_{(min,2)})$ *where,* $(U_1(\mathcal{L}_1) - D_{(min,1)})(U_2(\mathcal{L}_2) - D_{(min,2)})$ *is termed as the Nash product.*

Proof: As per Theorem 1, the joint utility set, Ψ is a non-empty convex set. To prove the existence of equilibrium, if the axioms (1)-(4) are satisfied, we infer that the bargaining problem has a unique solution as stated by Nash. The solution to the optimization problem gives the Nash bargaining solution. ∎

In case of m LPUs bargaining together, Theorem 2 cannot be applied directly. Hence, we increase the dimension of the convex set to m. The generalized optimization function is mathematically represented as:

$$\underset{(\gamma_1 L_1, \gamma_2 L_2, \cdots \gamma_m L_m)}{argmax} \prod_{i=1}^{m} (U_i(\mathcal{L}_i) - D_{(min,i)}) \tag{18}$$

such that, $(\gamma_1 L_1, \gamma_2 L_2, \cdots \gamma_m L_m) \in \Psi$ and $\gamma_i L_i \geq D_{(min,i)}$. The solution of the Generalized Nash Product as given in Equation (18) satisfies the four axioms in the m-dimensional space. Based on the solution to this bargaining process, the physiological parameters of the patient are transmitted by the LPU to the fog aggregation node or cloud.

V. Simulation Setup and Results

In this Section, we analyze the performance of the proposed scheme, CARE. The simulation parameters used for the experiment are listed in Table I. In our experiment, we consider the presence of 2-20 WBANs. We perform our analysis for 100 rounds with 95% confidence interval.

$$\nabla U_x(a_x^{t+1}) = -\frac{\mathbb{CI}_{W_x}\left(e^{\gamma_x^{t+1} a_x^{t+1} - \gamma_x^{min,t+1} a_{min,x}^{t+1}}\right)}{\left(1 + (\gamma_x^{t+1} a_x^{t+1} - \gamma_x^{min,t+1} a_{min,x}^{t+1})^2\right)\left(\tan^{-1}\left(e^{\gamma_x^{t+1} a_x^{t+1} - \gamma_x^{min,t+1} a_{min,x}^{t+1}}\right)\right)^2 \left(\gamma_x^{t+1} - \gamma_x^{min,t+1} a_{min,x}^{t+1}\right)} \tag{12}$$

$$\nabla U_x(b_x^{t+1}) = -\frac{\mathbb{CI}_{W_x}\left(e^{\gamma_x^{t+1} b_x^{t+1} - \gamma_x^{min,t+1} b_{min,x}^{t+1}}\right)}{\left(1 + (\gamma_x^{t+1} b_x^{t+1} - \gamma_x^{min,t+1} b_{min,x}^{t+1})^2\right)\left(\tan^{-1}\left(e^{\gamma_x^{t+1} b_x^{t+1} - \gamma_x^{min,t+1} b_{(min,x)}^{t+1}}\right)\right)^2 \left(\gamma_x^{t+1} - \gamma_x^{min,t+1} b_{min,x}^{t+1}\right)} \tag{13}$$

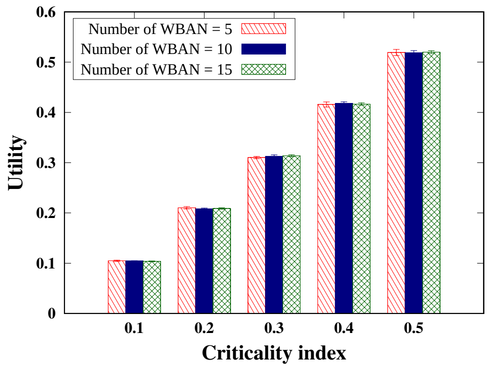

Fig. 2: Variation of Overall utility with Criticality index

Fig. 2 depicts the variation of the utility, $U_x(\mathcal{L}_x^{t+1})$ with

TABLE I: Simulation Parameters

Parameter	Value
Number of WBANs (N)	2 – 20
Number of types of sensor nodes in a WBAN	5
Drain efficiency (η)	15.7%
Path-loss exponent (α)	2
Constant value (ξ)	0.0005
Power consumption of transmitting circuit (P_{T_0})	$15.9mW$
Power consumption of receiving circuit (P_{R_0})	$22.2mW$

the criticality index of a patient. The x-axis represents the change in the criticality index with an interval of 0.1 in the presence of 5, 10 and 15 WBANs. The criticality of a patient is measured by the criticality index, and thus, the utility must increase with the increment of criticality index. Consequently, we observe an increasing trend in utility value with criticality. Additionally, the rate of increase in utility is almost similar in case of different number of WBANs.

Fig. 3 shows the comparison of the parameter values of various LPUs in our scenario. X-axis shows the *id* of the LPU present in the system. The parameter value includes the criticality index, and the maximum and minimum weightage provided to the LPU. We observe that the maximum value of weight factor of each LPU increases with the increase in

Algorithm 1 CARE

INPUTS:

1: ξ_{W_i} : Set of sensors attached to the W_i^{th} WBAN.
2: γ_x^{t+1} : Weight of x^{th} LPU at $(t+1)^{th}$ time instant
3: $\mathcal{L}$: Set of LPU's corresponding to each WBAN.
4: $\mathbb{CI}_{W_i}$: Criticality index of W_i^{th} patient.
5: Ψ: Joint utility set.
6: $\mathbb{D}$: Set of disagreement point.

OUTPUT:

1: F : Bargaining solution of $(\Psi, \mathbb{D})$.

PROCEDURE:

1: Weight given to m LPU's participating in the bargaining based upon $\mathbb{CI}$
2: **while** Ψ == non-empty convex set **do**
3: $U_x(L_x^t)$ is calculated. ▷ Utility of x^{th} LPU at time instant t.
4: m participating LPU's bargain among themselves
5: Satisfy the four axioms of Nash Bargaining process.
6: **end while**
7: Depending upon F, LPU transmits data either to the fog aggregation node or cloud.

TABLE II: System information for simulation time

Parameter	Value
Processor	Intel(R) Core(TM) i5-2400S CPU @2.50GHz
RAM	6GB
System type	64-bit OS, x64-based processor
Application software	MATLAB R2015a

criticality index. Similarly, the value of minimum weightage is also increased with the increasing range of criticality index. The patient with LPU 5 is most critical among all LPUs. Thus, the maximum weight of LPU 5 is highest.

The criticality of a patient is calculated using Equation (3). In this plot, we consider the total number of WBANs as 20, starting from 4 with an interval of 4. Based on the criticality of a patient, the physiological data of the patient are either transmitted to the cloud or fog node, which is decided by the outcome of the Nash Bargaining process. Therefore, the data dissemination delay may worsen the patient's condition. Fig 4 illustrates the combined analysis of data dissemination delay in case of traditional cloud and CARE. In this plot, we notice the data dissemination delay increases with the increase in the total number of WBANs in the system. However, irrespective of number of WBANs, the data dissemination delay is lesser in CARE as compared to the use of traditional cloud.

To evaluate the power consumption of each WBAN, we use the energy model given in [14]. The minimum power consumption to transmit data from the WBAN to the cloud or the fog aggregation node is mathematically expressed in Equation 19, where D_{ij} is the Euclidean distance between the WBAN and the cloud or fog aggregation node(d).

$$P_{T_i} = P_{T_0} + \frac{\xi \times D_{ij}^{\alpha}}{\eta} \tag{19}$$

Fig. (5) depicts the variation in power consumption of the networks using traditional cloud and CARE, in the presence

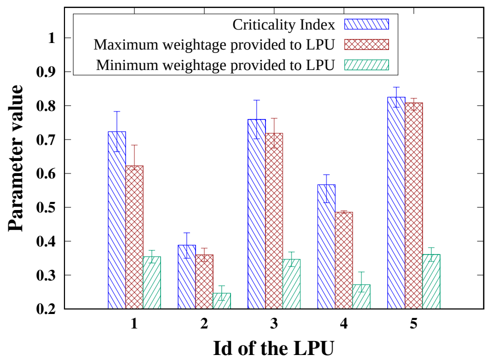

Fig. 3: Variation of Parameter values

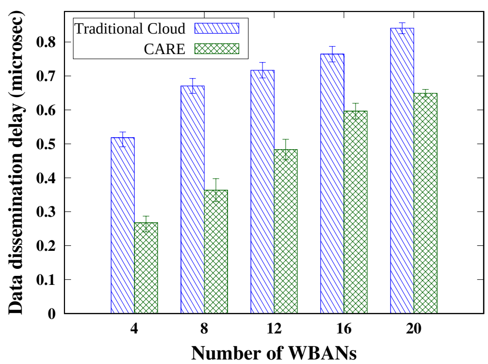

Fig. 4: Comparison of data dissemination delay with the number of WBANs

of $2-12$ WBANs. Along the x-axis represents the number of WBANs present in the system, which is incremented with an interval of 2. We notice that the total power consumption increases with the increase in the total number of WBANs in the system. However, using CARE, the power consumption is reduced by 30% (approximately) than that of traditional cloud.

The system specifications are represented in Table II, on which we experimented the performance of CARE. Fig. 6 shows the simulation time in case of 50 and 100 iterations for computation of he utility. The number of WBAN varies from $4-20$ along the x-axis. The simulation time varies from $0.001-0.0035$ seconds.

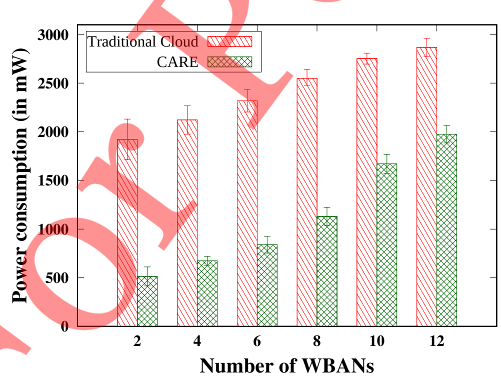

Fig. 5: Comparison of Power Consumption with number of WBANs

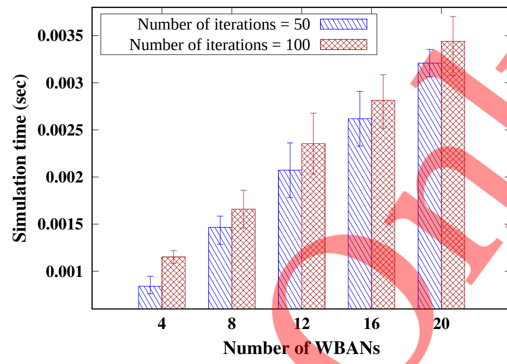

Fig. 6: Variation of Simulation time

VI. Conclusion

This work focused primarily on the criticality-aware physiological data transmission of a patient, in CPS-based healthcare systems. The main aim of this paper is to design a scheme to transmit the critical data to the fog node for quick processing through the available transmission unit. We used a cooperative game-theoretic Nash bargaining approach, in order to determine the selection of cloud or fog node for physiological data transmission. The results of comparative analysis show that the power consumption and data dissemination delay is lesser using CARE, as compared to the traditional cloud.

In the future, we plan to extend our work with real implementation of CARE in hospital scenario and ambulances. Privacy is an essential component in medical data. Thus, we plan to incorporate the privacy in the proposed scheme, CARE. In order to provide physiological data privacy, we plan to use hashing technique.

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