

# Soft-Health: Software-defined Fog Architecture for IoT Applications in Healthcare

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**Abstract**—In this paper, we propose a Software-defined fog architecture, named as Soft-Health, to serve various IoT-based healthcare applications. The health conditions of the patients fluctuate over time. Further, specialized medical care may not always be available in all healthcare facilities. The use of Wireless Body Area Network (WBAN) for continuous patient monitoring addresses the issue to a certain extent. However, as the physiological parameters of a patient are time-critical in nature, any delay, packet loss, and network overhead, may result in deterioration of the patient's health conditions. Considering this, we design a Software-defined fog-enabled IoT platform for various healthcare applications. We consider that the fog layer comprises SDN switches that allocate the packet to the appropriate fog/cloud depending upon the criticality index (CI) of the data packets originating from patients. We mathematically formulate the CI, based on the physiological parameters sensed and transmitted to the switches. Further, we design an optimization function to obtain the maximum utility of a fog node, for an optimal number of processes executed by that node. We apply the Lagrangian method to simplify the optimization function and solve it using Karush-Kuhn-Tucker (KKT) conditions. We apply the autoregression model to predict the total delay incurred and the total energy consumed by the proposed scheme. Exhaustive analysis of our proposed scheme, Soft-Health, demonstrates that the delay incurred decreases by 24.57% and 40.1% approximately, compared to the existing schemes, Mobi-Flow, and CARE, respectively.

**Index Terms**—Software Defined Network (SDN), Wireless Body Area Network (WBAN), Fog computing, Cloud computing, Health criticality.

## I. INTRODUCTION

WIRELESS Body Area Network (WBAN) [1] is a fundamentally important technology applied for developing IoT-based healthcare solutions. WBAN comprises a set of sensor/actuator nodes, which senses the health data of a patient and forwards the collected information to the destination devices (that may include servers), through a local processing unit (LPU) [1]- [2]. On the other hand, the health criticality of a patient may fluctuate at any time instant, therefore, continuous monitoring of the patient is necessary. Additionally, any delay incurred in processing these data may deteriorate the health conditions of the patient. The processing of a critical patient's data at the edge of the network minimizes the delay incurred in transmitting the data to the cloud/server [3].

On the other hand, a Software Defined Network (SDN) helps in the efficient utilization of the resources and network

management [4], [5]. The integration of an SDN with WBAN [6]- [7] results in the upgradation of the performance of the traditional WBAN. Further, to upgrade the performance of a WBAN and attain several objectives such as real-time processing and selection of the appropriate fog node to process the patient's data, optimal utilization of resources, and the placement of a minimum number of flow rules at the switches, is a challenging task. Considering these facts, we propose a Software-defined fog-enabled IoT platform for a diverse range of healthcare applications.

In the IoT-based healthcare applications [2]- [3], the physiological parameters of a patient are sensed by the sensor nodes and transmitted to the fog nodes/cloud, based on the health criticality of a patient. The processing of the physiological data in the cloud involves greater power consumption and delay compared to that in fog [3]. As the patients' data are time-critical in nature, therefore any delay in processing the data may deteriorate the patient's health conditions. Further, the criticality of a patient may vary at any time instant. During the transmission of patients' data to the cloud/server, various factors such as network overhead, throughput, packet loss, and latency, may affect the network performance. Therefore, it is important to address different issues such as processing the real-time information with minimum delay, utilizing the available resources properly, and maintaining the QoS parameters of the network, based on the critical conditions of a patient. We assess these facts and propose an SDN-enabled fog architecture consisting of controller and switches. The flow rules are designed by the controller and stored in the switches if the appropriate flow rule for a packet is unavailable. Further, depending on the flow rule, the switches forward the data packets to the cloud/fog for processing. Therefore, the major challenge is to minimize the processing time of the patient's data. Additionally, the selection of the appropriate fog node to store the optimal number of flow rules as well as minimize the number of interactions with the controller is a complex task, which we address in this proposed work.

In this proposed scheme, Soft-Health, we consider the time-critical nature of the physiological parameters of a patient and design the Software-defined fog-enabled healthcare platform. The primary motivation behind this proposed architecture is to minimize the processing time of the physiological data of the critical patients arriving at the switches. Based on the physiological data sensed by the WBAN, we estimate the criticality index. Further, the introduction of the fog layer in between the cloud and the WBAN minimizes the data processing time. The time-critical data that requires a prompt

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response is processed in the fog layer, otherwise, the data are transmitted to the cloud/server. We integrate the SDN along with the fog layer to minimize the delay incurred and improve the performance of WBAN. Typically, SDN consists of an SDN controller, which decides and updates the flow rules for the flow table present within the SDN switches. We design a utility function to estimate the overall benefit of the fog node. Flow rules are designed according to the utility value of the fog node present within the network. Furthermore, it is perceived that with the increase in the flow table memory size, the interactions between the controller and the switches decreases. However, with the increase in the memory size, the time required to serially search the appropriate flow rule in the flow table also increases. With the optimal number of flow rules, the number of interactions between the switches and the controller is reduced. As a result, the delay incurred to find the appropriate flow rule is minimized. In brief, the specific *contributions* of this work are as follows:

- We propose a Software-defined fog architecture for IoT applications in healthcare, which minimizes the processing time of the time-critical data packets arriving from the patient and provides prompt response.
- We formulate the criticality index of a patient depending on the value of the physiological parameters sensed by the WBAN to detect the health criticality of the patient. Based on the estimated criticality index, the data is processed at the fog nodes/cloud.
- We design the utility function for the fog nodes and formulate an optimization function to maximize their utility, based on the optimal number of processes executed by that node. To solve this optimization function, we apply Karush-Kuhn-Tucker (KKT) conditions.
- As per the existing flow rules and depending upon the maximum utility of the fog nodes, the switches select the appropriate fog node. In the absence of a flow rule, a new rule is introduced by the controller. To minimize the number of flow rules placed for an optimal number of interactions between the switches and the controller, we design an optimization function.

## II. RELATED WORK

In this section, we discuss some of the proposed schemes in the domain of healthcare [2], [3], [8] and SDN [5], [9], [10]. In a WBAN, the sensor nodes placed on the body of the patients continuously monitor their physiological parameters. Roy *et al.* [3] considered the health criticality of the patient and designed a fog-based healthcare platform. In this proposed scheme, depending upon the estimated criticality index of a patient, the sensed data is either transmitted to the cloud or fog nodes. Similarly, Paul *et al.* [11] proposed a scheme using fog computing to observe the patients suffering from chronic diseases. Further, Verma and Sood [12] proposed another model for remote monitoring of patients in smart homes, applying the concept of fog computing at the smart gateway. Additionally, the authors used data mining, distribution storage, and notification services at the edge of the network. In the IoT scenario, multiple radio protocol units may be present, which transmit the patients'

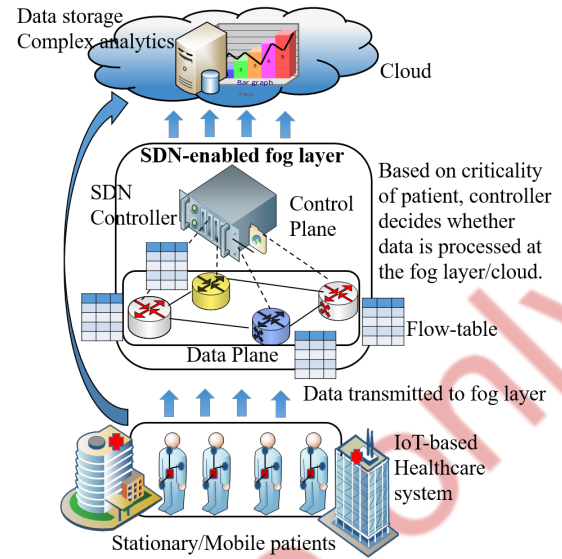


Fig. 1: Soft-Health: The System Architecture

sensed data to the server. Misra *et al.* [8] designed a scheme which dynamically selects the appropriate radio protocol.

The resources in a wireless sensor network are not utilized appropriately. Moreover, the vendors of WSN are rigid to policy changes and are quite difficult to manage. Considering these facts, Luo *et al.* [9] designed an SDN-based WSN architecture to introduce versatility, flexibility, and easy manageability into the traditional WSN architecture. On the other hand, to maximize the overall performance of the network, Bera *et al.* [5] proposed a mobility-aware adaptive flow-rule placement scheme in an SDN. The authors determined the optimal number of access points (APs) to minimize the cost related to the minimum number of flow rules placed. Further, Iqbal *et al.* [10] studied the IoT security requirements, challenges, and counteract them using SDN networks in various fields such as smart healthcare, smart control systems, and transportation.

Certain researchers proposed schemes describing the impact of IoT in the field of healthcare [13]–[16]. Qadri *et al.* [14] studied the various impacts of the IoT-based emerging technologies in the field of healthcare. The authors mentioned that SDN provides flexibility to the systems, while the integration of blockchain helps in securing them. In the IoT environment, the physiological data of the patients are necessary to be shared for processing and diagnosis. However, the medical data of patients are sensitive in nature and are prone to malicious attacks. Considering this fact, Meng *et al.* [16] proposed an SDN-based framework to secure the patient's data in a smart healthcare environment. Further, Rahman *et al.* [15] proposed a five-layered heterogeneous mist, fog, cloud-based healthcare platform for processing the patients in near-real-time. Additionally, the authors applied SDN and link adaptation-based load balancing for optimal allocation and efficient utilization of the available resource.

*Synthesis:* The analysis of the existing research works reveals that there exists a research lacuna of the selection of appropriate fog nodes among the heterogeneous types available, optimal utilization of available resources, and real-

time processing of data, considering the health criticality of a patient. The existing works in the field of SDN focus on the applications of SDN in traditional WSN [9] and adaptive flow-rule placement to maximize the overall network performance [5]. On the other hand, in a WBAN, the health criticality of the patient is considered, bargaining among CSPs and WBANs for resource allocation, and SDN-based WBAN [2], [3], [7], [17]. However, there exists no common platform, which considers the health criticality of the patient and the memory-constrained nature of the SDN switches. Considering these facts, we propose an SDN-enabled fog-based platform for healthcare IoT applications.

### III. SOFT-HEALTH: THE SYSTEM MODEL

#### A. System Architecture

We consider a traditional WBAN, where the sensor nodes sense and transmit the physiological parameters of the patient to a Local Processing Unit (LPU). Further, the LPU transmits the sensed data to the cloud/server. However, the health criticality of a patient may vary at any time instant. Based on the patient's health conditions, the physiological parameters are either transmitted to the fog/cloud [3]. The fog layer comprises fog nodes, which process the received physiological data of the patients incurring a minimum delay. The problem related to the fog nodes in the management of their heterogeneity. One of the possible solutions to these constraints is the integration of SDN and fog layer with the traditional WBAN. We consider that the patients are either static or mobile in our scenario, as illustrated in Fig. 1. Motivated by the SDN-enabled network architecture introduced by Cicioglu and Calhan [7], we propose a unique SDN-enabled fog-based platform for various IoT applications in the domain of healthcare. In the proposed architecture, the fog layer comprises OpenFlow switches [18] in the data plane along with the SDN controller in the control plane. These switches contain a set of flow rules, which are used to decide the routing path of the packet for further processing, based on the criticality index of the packet. The selection of the appropriate fog node is a complex task, if the data is necessary to be processed at the fog layer.

On the other hand, the flow rules are placed by the controller, and the criticality index range is divided into separate sub-ranges to identify the health criticality of a patient. The utility value of the fog node is also considered while designing the flow rules. On receiving the packets, the switches check the criticality index sub-range to which these packets belong to (i.e., how much critical is the patient's health condition?). Thereafter, the packet is allocated by the switch to the appropriate fog node for processing and the response is transmitted to the controller. On receiving the necessary information, the controller recomputes the utility value of the fog nodes and updates it among the switches. In case, a switch receives a packet of a particular criticality index for which none of the available fog nodes is capable of processing it, the switch transmits a packet-in signal to the controller. Then, the SDN controller searches for any newly introduced fog node, which does not possess any flow rule at that time instant. After the identification of the fog node,

the controller computes the utility value, generates flow rule, updates the flow table present in the switches, and allocates the packet for processing. Whenever a switch encounters a data packet within that utility value, it transmits that packet to the fog node for processing. The fog node on completion of the particular task transmits a signal to the controller via the nearest switch and waits for acknowledgment. If the controller does not receive the acknowledgment signal within a particular time interval, it re-sends the signal through other switches. On receiving the signal from the fog node, the controller transmits an acknowledgment signal, computes the utility value, and updates the flow rule in the switches.

#### B. Mathematical Formulation

Suppose a set of WBANs,  $\mathbb{W} = \{W_1, W_2, \dots, W_n\}$  is present in the scenario and  $\mathbb{S} = \{S_1, S_2, \dots, S_m\}$  be the set of sensor nodes attached to any WBAN. Each of the sensed data lies within the range of  $(\mathbb{D}_{min}, \mathbb{D}_{max})$ , where  $\mathbb{D}_{min}$  and  $\mathbb{D}_{max}$  represent the minimum and maximum values that a sensor node senses. Further,  $\mathbb{P}_{min}$  and  $\mathbb{P}_{max}$  represent the lower and upper normal sensed values of a patient. When the sensed value lies within the normal range, it is considered to be normal, while beyond this range, the sensed value is considered to be abnormal. The problem encountered by the above-mentioned approach is that any sensed value near to  $\mathbb{P}_{min}$ , but greater than  $\mathbb{P}_{min}$  is considered as normal and not incorporated in the estimation of the criticality index. Consequently, if the value drops constantly, but is greater than the normal range,  $\mathbb{P}_{min}$  or  $\mathbb{P}_{max}$ , is not considered. Therefore, to avoid this problem, we divide the normal range of the physiological sensor nodes into  $N$  equal slices. Further, we reformulate the normal minimum and maximum boundary values of the sensor nodes, considering  $g$  and  $h$  such that  $0 < g < h < N$  and  $\mathbb{P}_g$ , and  $\mathbb{P}_h$ , within the range of  $\mathbb{P}_{min}$  and  $\mathbb{P}_{max}$ . Any sensed value less than  $\mathbb{P}_g$  and greater than  $\mathbb{P}_h$  is considered as abnormal. Therefore,  $\mathbb{P}_g = \mathbb{P}_{min} + \frac{(\mathbb{P}_{max} - \mathbb{P}_{min})}{N}$  and  $\mathbb{P}_h = \mathbb{P}_{max} - \frac{(\mathbb{P}_{max} - \mathbb{P}_{min})}{N}$ .

By redefining the limit, we avoid the sudden fluctuation in the patient's health condition. If the sensed data lies outside this range, then the patients' condition is considered to be critical. Motivated by the concept of criticality index proposed by Roy *et al.* [3], we mathematically represent the criticality index for each of the patients as,

$$\mathbb{CI}_{W_i} = \frac{1}{\alpha} \left( \sum_{a=1}^x \frac{(\mathbb{P}_g^a - \mathbb{O}_c^a)^2}{(\mathbb{P}_g^a - \mathbb{D}_{min}^a)^2} + \sum_{b=1}^y \frac{(\mathbb{O}_c^b - \mathbb{P}_h^b)^2}{(\mathbb{D}_{max}^b - \mathbb{P}_h^b)^2} \right) \quad (1)$$

where  $\mathbb{O}_c^a$  and  $\mathbb{O}_c^b$  represent the observed physiological parameter of the  $a^{th}$  and  $b^{th}$  patient.  $\alpha$  denotes the number of sensor nodes attached to the  $W_i^{th}$  WBAN. The number of sensor nodes, whose values are less than the lower normal value and greater than the upper normal value is denoted as  $x$  and  $y$ , respectively.

Based on the  $\mathbb{CI}$ , the data are processed at the fog node/cloud. In case of a critical patient, the particular fog node is selected for processing that data. On receiving the data packet, the SDN controller declares and updates the flow rule among the switches. Therefore, for the selection

of the appropriate fog node, we design the utility of the fog nodes. Roy *et al.* [17] defined the utility of fog nodes in terms of the available storage space, average number of tasks executed, distance between the fog nodes and sensor nodes, and feedback provided to that fog node. However, the authors do not consider the bandwidth and energy consumed, which are also important parameters. Motivated by their utility function designed to dynamically select the fog node, we define the utility function of the  $i^{th}$  fog node as:

$$\mathbb{U}_i = \left( \lambda_1 S_i^{t,eff} + \lambda_2 (N_i^{t,avg})^m + \lambda_3 B_i^{t,eff} \right) \times \left( \frac{\lambda_4}{D_{ij}^{eff}} + \frac{\lambda_5}{E_i^{t,eff}} \right) \quad (2)$$

where  $\lambda_1, \lambda_2, \lambda_3, \lambda_4,$  and  $\lambda_5$  are the weight factors such that  $\forall i = \{1, 2, 3, 4, 5\}$  and  $0 < \lambda_i < 1$ .  $S_i^{t,eff}, N_i^{t,avg}, B_i^{t,eff}, D_{ij}^{eff}$ , and  $E_i^{t,eff}$  represent the effective storage space, average number of tasks executed, effective bandwidth, distance between the fog nodes and the switches, and effective energy consumed, respectively. The power  $m$  is mentioned in average number of processes executed to provide importance to that parameter. Besides distance, storage and average number of task executed, used in the utility function, proposed by Roy *et al.* [17], the effective bandwidth available and the energy consumption by a particular fog node is also crucial for estimating the delay incurred and energy consumed by that fog node. We incorporate these factors while designing the utility function. We express  $S_i^{t,eff}$  as the ratio of the available storage space of the  $i^{th}$  fog node at time instant,  $t$ , to the maximum storage space of the fog nodes,  $S_i^{max}$ . Mathematically,  $S_i^{t,eff} = \frac{S_i^t}{S_i^{max}}$ . Further, the average number of process executed  $N_i^{t,avg}$  at the  $i^{th}$  fog node is expressed as the ratio of the sum of the total number of processes executed till time instant,  $T$ , to the maximum number of processes executed by the fog nodes,  $N^{max}$ . Therefore,  $N_i^{t,avg} = \frac{\sum_{i=1}^T N_i^t}{N^{max}}$ . Similarly, we estimate the effective bandwidth,  $B_i^{t,eff}$  of the  $i^{th}$  fog node in terms of the bandwidth of that fog node to the maximum bandwidth,  $B_i^{max}$  at time instant,  $t$ . Mathematically,  $B_i^{t,eff} = \frac{B_i^t}{B_i^{max}}$ . The effective distance,  $D_{ij}^{eff}$ , between the  $i^{th}$  fog node and the  $j^{th}$  switch is expressed as the ratio of the distance between the fog node and switch to the maximum allowable distance between the  $i^{th}$  fog node and the  $j^{th}$  switch, beyond which the fog node and the switch is unable to communicate among them. Therefore,  $D_{ij}^{eff} = \frac{D_{ij}^t}{max(D)}$ , where the function  $max(D)$  returns the maximum value of distances between the  $i^{th}$  fog node and the switches. Further, the effective energy consumed is represented as,  $E_i^{t,eff} = \frac{E_i^t}{E_i^{in}}$ , where  $E_i^t$  is the energy consumed during time instant,  $t$  and  $E_i^{in}$  is the initial energy of the  $i^{th}$  fog node. Therefore, the optimization function to maximize the utility of each fog node, as illustrated in Equation (2), is mathematically represented as,

$$\operatorname{argmax}_{N_i^{t,avg}} \mathbb{U}_i \quad (3)$$

subject to,  $0 \leq (S_i^{t,eff}, B_i^{t,eff}, D_{ij}^{eff}, E_i^{t,eff}) \leq 1$ , and

$N_i^{t,avg} \leq N_i^{max,t}$ , where  $N_i^{max,t}$  is the maximum number of processes executed by the  $i^{th}$  fog node at time instant,  $t$ .

To simplify the optimization function given in Equation (3), we apply *Lagrangian* function which is represented as,

$$\mathbb{L}_i = \mathbb{U}_i - \mu_1(1 - S_i^{t,eff}) - \mu_2(1 - B_i^{t,eff}) - \mu_3(1 - D_{ij}^{eff}) - \mu_4(1 - E_i^{t,eff}) - \mu_5(N_i^{max,t} - N_i^{t,avg}) \quad (4)$$

where  $\mu_1, \mu_2, \mu_3, \mu_4,$  and  $\mu_5$  are the *Lagrangian Multipliers*. Further, we apply *Karush-Kuhn-Tucker* (KKT) conditions [19] to obtain the optimal value of  $N_i^{t,avg}$ . The *dual feasibility* and *complementary slackness* conditions are as follows:

$$\nabla_{N_i^{t,avg}} \mathbb{L}_i = 0, \mu_i(X) = 0, \text{ and } \mu_i \geq 0 \quad (5)$$

and  $X$  represent the constraints of Equation (3) and  $\forall i = \{1, 2, 3, 4, 5\}$ . On solving Equation (5), we obtain the optimal value of the number of processes executed, as given in Equation (6).

$$N_i^{t,avg*} = \left( \frac{\lambda_2 m}{\mu_5} \right) \left( \frac{\lambda_4}{D_{ij}^{eff}} + \frac{\lambda_5}{E_i^{t,eff}} \right)^{\frac{1}{(m-2)}} \quad (6)$$

**Corollary 1.** *Utility function of the  $i^{th}$  fog node is maximum when the  $S_i^{t,eff}, N_i^{t,avg}$ , and  $B_i^{t,eff}$  are maximum, and  $D_{ij}^{eff}, E_i^{t,eff}$  are minimum.*

Please find the proof in the supplementary file.

On the other hand, the total energy consumed,  $E$  comprises the energy consumed for sensing and transmitting the physiological data, processing these data, and generating flow-rule at the switches. Based on the flow-rule,  $F_R$  placed at the switches, the patient's data are processed either at the fog nodes or cloud, which is mathematically represented as,

$$F_R = \begin{cases} x, & \text{new flow-rule introduced; controller decides} \\ & \text{whether data is to be processed at the fog/cloud.} \\ y, & \text{patient's data is processed at the fog nodes.} \\ z, & \text{patient's data is processed at the cloud.} \end{cases} \quad (7)$$

Further, the energy consumed for sensing and transmitting the data by a WBAN and processing them at the fog nodes/cloud are represented in Equation (8) and (9).

$$E_{W_i} = \sum_{j=1}^m \sum_{i=1}^n (E_{S_{j_i}} + E_{T_{j_i}}), \forall W_i \in \mathbb{W} \text{ and } S_j \in \mathbb{S} \quad (8)$$

$$E_{f_c} = \begin{cases} E_{sw} + E_c, & \text{flow-rule} = z \\ E_{sw} + E_{ctr_s}, & \text{flow-rule} = y \\ E_{sw} + E_{ctr}, & \text{flow-rule} = x \end{cases} \quad (9)$$

Therefore, the effective energy consumed is denoted as  $-E^{eff} = \frac{E_{fc} + E_{W_i}}{E^{thres}}$ , where  $E_{fc}$  represents the total energy required by the switches for processing the sensed data either at the fog node/switches or in the data plane/cloud.  $E_{sw}$  and  $E_c$  are the energy required to process data at the switch and forward them to the fog node, and process data at the cloud. The energy required by the controller to generate the flow rules and maintain the quality of service (QoS) is denoted by  $\mathbb{E}_{ctr}$ .

The total delay in the network is represented as the sum of the time taken for sensing and transmitting the sensed data by WBAN,  $T_{W_i}$  and time required to process the sensed data at the fog nodes/cloud,  $T_{f_c}$ . In case of the absence of routing information in the flow rules, we consider the delay incurred to transmit a signal to the controller, regarding the arrival of a new data packet. Thereafter, the controller designs the flow rule and accordingly transmits the packets to the fog node/cloud for processing. The delay incurred for sensing, processing, and transmission of the data packet from the  $i^{th}$  WBAN is,

$$T_{W_i} = \sum_{b=1}^m \sum_{a=1}^n (T_{S_{ba}} + T_{t_{ba}}), \forall W_i \in \mathbb{W} \text{ and } S_b \in \mathbb{S} \quad (10)$$

Further, the delay incurred for processing the data at the fog nodes/cloud is represented as,

$$T_{f_c} = \begin{cases} T_{sw} + T_c + T_{trans_c}, & \text{flow-rule} = z \\ T_{sw} + T_{f_s} + T_{trans_{sw}}, & \text{flow-rule} = y \\ T_{sw} + T_{ctr} + T_{trans_{ctr}}, & \text{flow-rule} = x \end{cases} \quad (11)$$

where  $T_{f_c}$  represents the total time taken by the switches to process the sensed data at the fog nodes or cloud.  $T_{sw}$  is the time taken by each switch to forward the data to the appropriate fog node. Further, the time required to process the physiological data in the cloud is denoted as  $T_c$ .  $T_{ctr}$  and  $T_{f_s}$  are the time taken by the controller to generate the flow rules and the fog server within which the SDN controller resides. Therefore, the total delay incurred is mathematically represented as  $-T^{eff} = \frac{T_{W_i} + T_{trans_{sw}} + T_{f_c}}{T^{thres}}$ . Typically, Nakagami-m distribution is used to compute the attenuation of wireless signals which traverse through multiple paths. Additionally, this distribution also identifies the impact of fading channels. However, in real test-bed implementation of Soft-health, the sensor nodes are connected through wires to the Local processing unit (LPU). The criticality index is calculated and transmitted through a wireless communication medium to the server. Hence, the sensor placement, ambient noise in the patient's environment, and transmission frequency of the sensor nodes do not significantly affect the overall transmission delay.

In this proposed work, based on the CI, the patient's data are processed at the cloud/fog. Further, depending upon the flow rules placed by the controller, the switches select the appropriate fog node for processing the data. In the absence of proper flow rule, the switch interacts with the controller. Therefore, optimization of the number of flow rules,  $N_R$ , and interactions  $M_c^i$  between the switches and the controller is essential. We define,  $N_R = f(\text{CI}_{W_i}, E_{W_i}, T_{W_i}, M_c^i)$ . To minimize the overhead for generating the flow rules for transmitting the data packets to the cloud/fog nodes for processing, we design an optimization function, which is represented as,

$$\underset{M_c^i}{\text{argmin}} \quad N_R \quad (12)$$

subject to,  $\text{CI}^{min} \leq \text{CI}_{W_i} \leq \text{CI}^{max}, \forall W_i \in \mathbb{W}, E^{min} \leq E_{W_i} \leq E^{max}, \forall W_i \in \mathbb{W}, T^{min} \leq T_{W_i} \leq T^{max}, \forall W_i \in \mathbb{W}$ , and  $M_c^i < M_c^{i,max}$ .  $\text{CI}^{min}$ ,  $\text{CI}_{W_i}$ , and  $\text{CI}^{max}$  represent the minimum value of criticality index, criticality index of

the  $i^{th}$  WBAN's data, and the maximum value of criticality index, respectively. Similarly,  $E^{min}$ ,  $E_{W_i}$ , and  $E^{max}$  denote the minimum energy required, energy consumed to process the  $i^{th}$  WBAN's sensed data, and the maximum energy consumed, respectively. Finally,  $T^{min}$ ,  $T_{W_i}$ , and  $T^{max}$  represent the minimum delay incurred in transmitting the data packets, total delay incurred by the  $i^{th}$  WBAN's sensed data, and the maximum delay occurred. To simplify Equation (12) w.r.t the constraints, we apply *Lagrangian* function such that,

$$\mathcal{L} = N_R - \nu_1(\text{CI}^{max} - \text{CI}_{W_i} - \text{CI}^{min}) - \nu_2(E^{max} - E_{W_i} - E^{min}) - \nu_3(T^{max} - T_{W_i} - T^{min}) - \nu_4(M_c^{i,max} - M_c^i) \quad (13)$$

where  $\nu_1$ ,  $\nu_2$ ,  $\nu_3$ , and  $\nu_4$  are the Lagrangian Multipliers. Further, we solve Equation (13) using Karush-Kuhn-Tucker (KKT) conditions. The *dual feasibility* and *complementary slackness* conditions are as follows:

$$\nabla_{M_c^i} \mathcal{L} = 0, \nu_i(X) = 0, \text{ and } \nu_i \geq 0, \forall i = 1, 2, 3, 4 \quad (14)$$

On solving the KKT conditions given in Equation (14), we obtain the optimal number of interactions for which the minimum number of flow rules are placed by the controller.

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#### Algorithm 1 Soft-Health

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**INPUT:** Sensed physiological data from WBAN

**OUTPUT:** Processing of data at the cloud/appropriate fog node

**PROCEDURE:**

- 1: **for**  $k = 1$  to  $n$  **do** ▷  $n$ : Number of WBANs
  - 2:   Compute  $\text{CI}_{W_k}$  as per Equation (1).
  - 3:    $F = f(\text{CI}_{W_k})$  ▷ Estimate the header to be appended with the packet during transmission
  - 4:   **for**  $j = 1$  to  $N_R$  **do** ▷  $N_R$ : Number of flow rules
  - 5:     **if** ( $F = \text{Flowrule}_j$ ) **then**
  - 6:       **if** ( $\text{Flowrule}_j = \text{ComputeInFog}$ ) **then**
  - 7:          Select fog node, as per Equation (2)
  - 8:          Update  $\mathbb{U}_i$  using selected information
  - 9:          Compute data in selected Fog node
  - 10:       **else**
  - 11:          Compute data in cloud
  - 12:       **end if**
  - 13:     **else if** ( $\text{Flowrule} = \text{Not Found}$ ) **then**
  - 14:       Send the packets to the controller
  - 15:        $\text{NewFlowrule} = \text{Generate new flow rule}$
  - 16:        $\text{loc} = \text{Allocate the flow rule in a appropriate location within the flow table and repeat steps 7-10.}$
  - 17:     **end if**
  - 18:   **end for**
  - 19: **end for**
- 

Algorithm 1 illustrates the comprehensive view of the selection of the appropriate fog node/cloud, where the sensed data of the patient is to be processed. For each WBAN data, the criticality index is estimated and appended with the header of the data packet, as discussed in Step 2. The switch on receiving the data packet searches for the matching flow rule. If the data needs to be processed in the fog node, then  $\mathbb{U}_i$  is computed and the packet is transmitted to the appropriate fog node for

processing, as shown in Steps 5-9. Step 11 depicts that the packet is transmitted to the cloud for further processing. If the appropriate flow rule is not available in the switch, then it is transmitted to the controller. The controller designs the appropriate flow rule and updates the switches as demonstrated in Steps 13–16. Further, the minimum number of flow rules to be placed by the controller with the optimal number of interactions between the controller and switches is obtained from Equations (13) and (14).

**Corollary 2.** *If  $T$  be the time required to match the sensed physiological data with a single flow rule and  $K$  represents the matching rule position in the flow table, then the total time required to search the rule serially up to  $k^{\text{th}}$  position is  $T_{\text{tot}} = \sum_{i=1}^k (T_i)$ .*

Please find the proof in the supplementary file.

From the above stated Corollary 2, it is evident that the greater the size of the table, the more is the number of comparisons required to get the matching rule, which thereby incurs delay. Hence, it is necessary to minimize the number of flow rules,  $N$ , present in the flow table to reduce the latency incurred for searching a particular flow rule in the flow table. This is achieved by replacing the least used flow rules with the most used ones by the transmitted data packets from the WBANs.

**Corollary 3.** *The smaller the size of the flow table, the lesser is the probability of matching flow rule in the flow table, thereby increase in the number of interactions.*

Please find the proof in the supplementary file.

#### IV. PERFORMANCE EVALUATION

##### A. Simulation Design

In order to analyze and evaluate our proposed scheme, Soft-Health, we use the POX controller, Mininet, and Python as the emulator tool to simulate our proposed scenario. We assume the mobility model of the fog nodes as constant. **We use real-time physiological data of patients for analysis of our proposed scheme. The WBAN unit attached to the patients comprises pulse, ECG, and temperature sensors, which sense and transmit them to the LPU placed.** The various simulation parameters considered for the evaluation of the performance of our proposed scheme is listed in Table I.

##### B. Results

In this section, we use different performance metrics such as delay, energy consumption, and criticality index to evaluate and analyze the performance of the proposed scheme.

**Criticality Index:** Fig. 2(a) illustrates the variations in the criticality index of 3 patients at various time instants. We observe that the health criticality of the patients fluctuates randomly with time. The CI of a patient is estimated using Equation 1. Additionally, the health conditions of the WBAN,  $W1$  attached to the patient seem to be more critical compared to WBAN,  $W2$  and  $W3$ , over the entire time period. However,  $W2$  and  $W3$  are critical over the time duration 50–60 minutes. On the other hand, we observe that the fluctuations in the

effective delay incurred and energy consumed for the WBANs  $W1$ ,  $W2$ , and  $W3$ , are also random. The delay incurred and energy consumed by these WBANs to sense and transmit the physiological data of the patients to the server also vary with time. Therefore, we conclude that the health criticality of a patient, the energy consumed, and the delay incurred in transmission of the sensed data fluctuates randomly with time.

TABLE I: Simulation Parameters

Parameter	Value
Simulation area	1000 × 1000 $m^2$
Number of WBAN nodes	10-50
Type of sensors in a WBAN	3
Maximum sensors in a WBAN	8
Number of switches	5 - 30
Number of flow rules	1,000
Deployment type	random

**Delay incurred:** The integration of SDN and fog layer with the traditional WBAN results in the minimization of the effective delay incurred by the proposed scheme, as demonstrated in Figs. 2(b) and 3(a). We observe that the effective delay incurred in transmitting the data of the three WBANs,  $W1$ ,  $W2$ , and  $W3$ , varies randomly with time, with the fluctuation in their respective CI. The probable reason behind this is that when a patient recovers and is stable, the data are transmitted to the cloud for processing, which increases the delay incurred. In Fig. 3(a), we observe that the effective delay incurred using Soft-Health is significantly reduced compared to the existing schemes, Mobi-Flow [5], CARE [3] and **Fog-IoT [12]** by 41%, 29% and 27% (approx.). One of the possible reasons behind this is that the transmission, processing, and analysis of the data in the cloud layer consumes more time compared to the data processed at the edge. In the case of Soft-Health, with the integration of SDN and the fog layer, the controller gets the global view of the network and significantly minimizes the delay incurred in the network, by reducing the delay in processing the data in the cloud. On the other hand, in the case of CARE, the delay incurred is comparatively less compared to Mobi-Flow, due to the presence of the fog layer. The authors in CARE [3], processed the physiological data at the fog layer/cloud, based on the health criticality of the patient. Therefore, in our proposed platform, the integration of SDN as well as fog layer together with the traditional WBAN, minimizes the total delay incurred compared to the existing schemes.

**Energy consumption:** Figs. 2(c), 3(b), and 3(d) demonstrate the variations in the energy consumed with time instants, and increase in the number of switches and WBANs. We observe that the effective energy consumed is reduced by 3.89%, 12.16% and 6.5% compared to CARE [3], MobiFlow [5] and **Fog-IoT [12]** respectively, with the increase in the number of switches. We observe that with the increase in the number of WBANs, the effective energy consumed increases. This is because, with the fluctuation in the health conditions of a patient, the data is processed at the fog layer, which consumes less energy. On the other hand, whenever the patient recovers

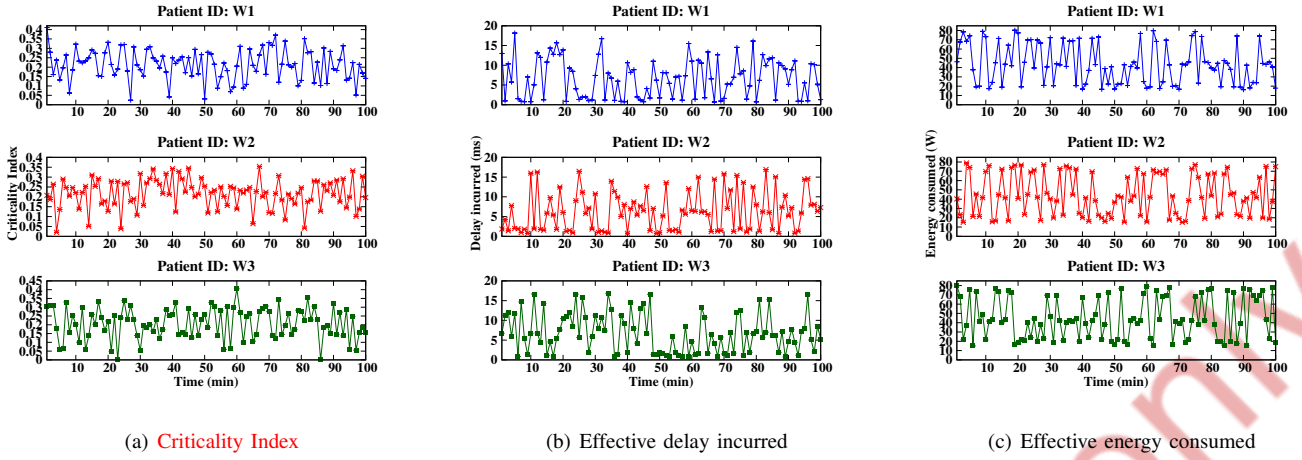


Fig. 2: Variation of criticality index, effective energy consumed, and effective delay incurred

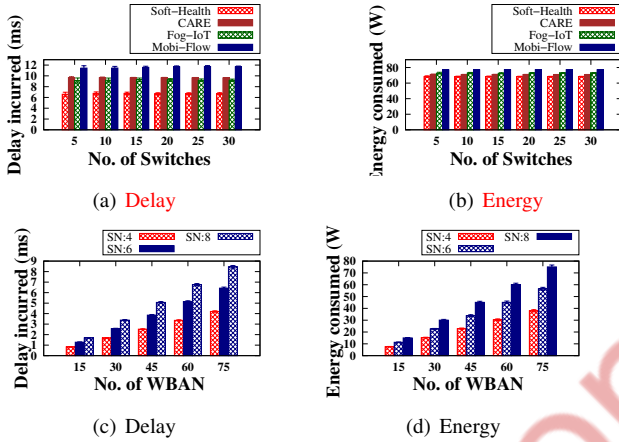


Fig. 3: Effective delay incurred and energy consumed with the number of switches and WBANs

and is stable, the data are processed in the cloud, which leads to greater energy consumption. The proposed scheme processes the data in the appropriately selected fog node, thereby eliminating the necessity to transmit and process the data in the cloud. Based on the health criticality of the patient, the flow rules are updated at the switches by the controller. In the existing scheme, Mobi-Flow [5], the absence of a fog layer increases the energy consumption.

*Utility of Fog node:* Fig. 4 illustrates the variations in the utility of the fog node with the change in the distance between the fog nodes and the switches, effective energy, and the available storage space in the fog node. We observe a decreasing trend in the utility of the fog node with the increase in the distance between the fog node and the switches, and energy consumption, as demonstrated in Figs. 4(a) and 4(b). On the other hand, we observe that the utility increases with the increase in the available storage space in the fog node, as illustrated in Fig. 4(c). The probable reason behind this is that with the increase in the distance and energy, the probability to select a fog node is reduced, thereby decreasing the utility of that node. On the other hand, with the increase in the available

storage space, the chances of selecting the fog node increase.

*Number of flow rules:* The energy consumption and the delay incurred with the increase in the number of flow rules is illustrated in Figs. 5(a) and 5(c) respectively. We observe that with the increase in the number of flow rules, both the energy consumption and delay incurred increase. However, after reaching a certain level, a decrease in the energy consumption and the delay incurred is noticed. This is because, in the beginning, as the flow rules are not available in the flow table, the interaction with the controller is frequent. Therefore, the energy consumption and delay incurred increase. With the placement of flow rules in the flow tables, the interactions between the controller and the switches is reduced, which minimizes the energy consumption and delay. Figs. 5(b) and 5(d) demonstrate the prediction in the energy consumption and delay incurred applying the autoregression model. We observe that the energy consumed and delay incurred using our proposed scheme is almost the same as predicted by the autoregression model.

## V. CONCLUSION

In this paper, we propose a Software-defined fog architecture for applications in healthcare IoT scenario. The physiological data of the patient are sensed and transmitted to the cloud/server for further processing in a WBAN. The proposed scheme, Soft-Health, integrates SDN and fog computing features to minimize the effective time required for processing the physiological data transmitted by WBANs and suggests actions to be taken, depending on the health conditions of the patient. On the other hand, the integration of SDN addresses the vendor-specific heterogeneity problems experienced by the fog nodes and improved management of resources, due to the increase in the number of WBANs. We estimated the criticality index of the patients to decide whether to process the data at the fog nodes/cloud. The utility value of each fog node is used to compute their efficiency. Additionally, the utility is used to select the appropriate fog node, which is capable of processing the data. Further, we also minimize the number of flow rules placed using the optimal number of interactions between the controller and switches.

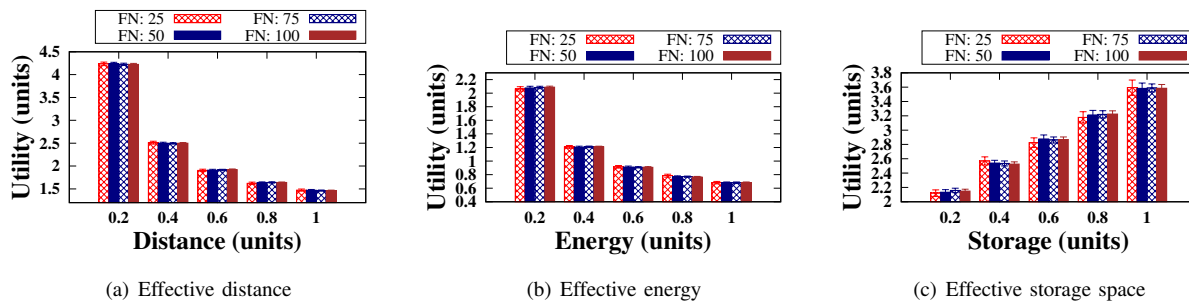


Fig. 4: Variation of utility with different parameters

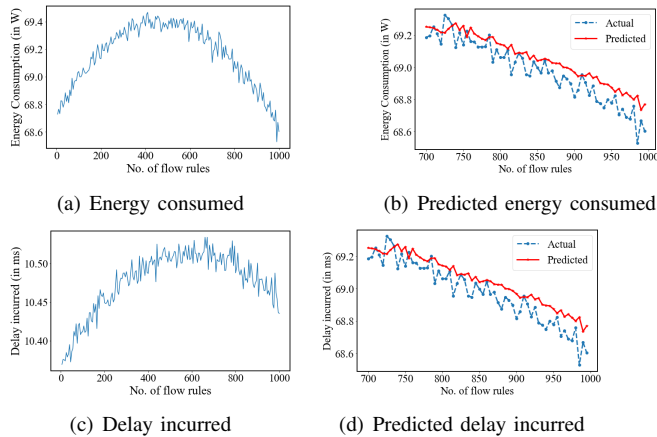


Fig. 5: Variation of energy consumed and delay incurred

In the future, we plan to implement our proposed scheme in real-life and integrate deep learning-based methods to process and provide the accurate decision to the patients. Furthermore, as the SDN switches are resource-constrained in nature, we intend to design an appropriate flow rule placement algorithm, which replaces certain flow rules that are not frequently used. Therefore, the excess time required for designing the flow rules is reduced, which results in a significant reduction in the delay incurred, energy consumption, and improved resource management.

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