CONGESTION CONTROL FOR DIFFERENTIATED HEALTHCARE SERVICE DELIVERY IN EMERGING HETEROGENEOUS WIRELESS BODY AREA NETWORKS

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ABSTRACT

Rapid advances in Information and Communications Technologies are enabling the wide diffusion of healthcare systems which allow a continuous remote patient monitoring and diagnostics by doctors. The need for pervasive and ubiquitous healthcare services has accelerated the development of heterogeneous communication architectures that integrate one or more different types of wired and wireless network technologies such as those used in the Internet, and in cellular, wireless body networks, and ad hoc networks. However, these modern healthcare systems have established some additional critical requirements and challenges, compared to traditional wireless networks, such as reliability and the timely access to diagnostic information without failure. The main aim of this article is to propose a healthcare traffic control over the modern heterogeneous wireless network to avoid congestion phenomena and guarantee QoS (Quality of Service) in terms of service reliability and responsiveness. First, a proportional fair allocation control strategy at each healthcare terminal device/router is implemented to regulate the rate of data flow proportionally to the information priority. The priority can be related to both the bandwidth requirement for the reliable communication of a vital signal and to the level of emergency in specific acute care, clinical disease and outbreak/disaster situations. Secondly, we present a congestion control based on the adaptive fairness criterion that can deal with differentiated and dynamic healthcare scenarios. A simulator environment has been built to validate the effectiveness of the proposed approaches.

INTRODUCTION AND RELATED WORK

The recent increased interest in distributed and flexible wireless pervasive applications has focused great attention on the QoS (Quality of Service) requirements of WNCS (Wireless Network Control System) architectures based on WSANs (Wireless Sensor Actuator Networks). Wireless data communication networks provide reduced costs, better power management, easier maintenance and an effortless deployment in remote and hard-to-reach areas. Although WSAN research was originally undertaken for military applications, as the field has slowly matured and the technology rapidly advanced, it has been extended to many civilian applications such as environment and habitat monitoring, home automation, traffic control, and more recently healthcare applications. In particular, WBAN (Wireless Body Area Network) technology has recently significantly increased the potential of cooperative systems and remote healthcare monitoring systems (e.g. see i.e. [1, 2] and the references therein). A WBAN is a particular kind of WSAN consisting of strategically placed wearable or implanted (in the body) wireless sensor nodes that transmit vital signs (e.g., heart rate, blood pressure, temperature, pH, respiration, or oxygen saturation) without limiting the activities of the wearer. The data gathered can be forwarded in real time to the hospital, clinic, or central repository through a LAN (Local Area Network), WAN (Wide Area Network) or cellular network. Doctors and carers can at a distance access this information to assess the state of health of the patient. Additionally, the patient can be alerted by using SMS, alarm, or reminder messages. In a more advanced WBAN, a patient's sensor can even use a neighboring sensor to relay its data if the patient is too far away from the central server (e.g. the hospital data storage). This communication mode is called ''Multi-hop'' wireless transmission. Generally speaking, multi-hop not only extends the communication distance but also saves energy consumption since direct sensor-server long distance wireless communication is avoided through hop-to-hop relay. WBANs will become increasingly pervasive in our daily lives. Recently, WBAN technology has significantly increased the potentiality of remote healthcare monitoring systems ([3, 4]). The patient is integrated with multiple sources of measurement, POC (Point Of Care)

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devices, enabling individuals to accurately, easily, and efficiently generate and collect healthcare data (see [5] and the references therein). Transmission needs to be performed to communicate the collected physiological signals from the POC devices to the sink node (e.g. a PDA, smartphone, or custom designed microcontroller-based device with routing functionalities) and possibly to send the aggregated measurements to a remote medical station. The POC nodes form a cluster of the Wireless Body Area Network (WBAN) and are usually in the basic configuration of a star topology as in Fig. 1, transmitting information to the router sink node that provides the functionality of collecting the data and routing them to the remote station (e.g. the hospital terminal) by a Wireless Mesh Network (WMN). There is a wide variety of available wireless technologies and distributed control techniches that can provide and support a data transmission between the sink node and a remote station such as WLAN, GSM, GPRS, UMTS, and WiMAX. On the other hand, examples of wireless communication standards utilized for short range intra-BAN communication (between the POC node and sink terminal) are IEEE 802.15.1 (Bluetooth 1, 6]) and 802.15.4 (i.e. Zigbee [1, 7]). Recently, the 802.15.6 IEEE Task Group [8] has been planning the development of an optimized communication standard aimed at defining a BAN that works at a range even shorter than the other wireless technologies that are already available on the market. The overall heterogeneous wireless communication network architecture supporting healthcare delivery is shown in Fig. 1. This modern healthcare system establishes the critical requirement of avoiding congestion phenomena that strongly degrade the quality of healthcare services.

The problem of congestion, due to the uncontrolled increase of traffic with respect to the network capacity, is one of the most serious phenomena affecting the reliability of the transmission of information and the loss of packets in any network. Therefore, it is a critical issue, especially in healthcare systems transmitting vital signs, to design an appropriate control strategy addressing reliability and timely delivery without failure. In addition, in wireless sensor networks, congestion increases the dissipated energy at the sensor node. In many healthcare applications (e.g. fetal electrocardiogram monitoring, and tele-cardiology), communication links carry vital information between the patient and the monitoring devices, that needs to be transmitted in short bursts, requiring a reliable connection. Therefore, it is a critical issue, especially in healthcare systems, to design an appropriate protocol solution addressing reliability, the timely access to patient information, energy efficiency, scalability, and reduced packet losses. The basic approach to congestion avoidance is to control the POC flow rate device by placing some simple queue based or autonomous learning machines at each of the nodes ([9] and the references therein). Other approaches propose the scheme of priority for telemedicine/e-health services in the case of ECG (Electro-Cardio-Gram) devices ([10]) and, more generally, for WiFi protocols (see [11] and the references therein). In this article, we propose a flow control to avoid congestion in the modern heterogeneous wireless network supporting healthcare service delivery. The control guarantees a good level of QoS with the service differentiated among different vital sign flows. Specifically, we plan to mitigate the congestion problem by implementing a proportional fair allocation control strategy at each terminal node to regulate the rate of data flow at the POC nodes proportionally to their priority. Additionally, we assess the promising advantage in adopting adaptive fairness criteria to manage services in remote healthcare systems. Finally, we discuss a simulator environment which we have built to validate the effectiveness of the proposed approaches. The simulation environment includes the main vital signs and wireless network protocol modeling. The potential impact within healthcare remote system applications might be interesting for the following two reasons. First, with the increasing use of POC technologies, future healthcare networks will include more and more heterogeneous wireless technologies and performing POC devices. The heterogeneity is in respect of both the kind of vital signs monitored and the bandwidth requirement for a reliable communication. Secondly, during large-scale disasters and/or medical emergencies, it is quite likely that the sensors placed in the different patients, will sense and transmit vital patient information very frequently and simultaneously, leading to an increased likelihood of congestion (examples include natural calamities such as earthquakes, the spread of epidemic diseases, or disasters due to human acts, such as the 9/11 terrorist attacks). In all the aforementioned scenarios, congestion can lead to the dropping of packets, and an increased consumption and reduction of the throughput. The present work might impact on both the reliability of the healthcare system and on the management of the heterogeneous wireless technologies support-

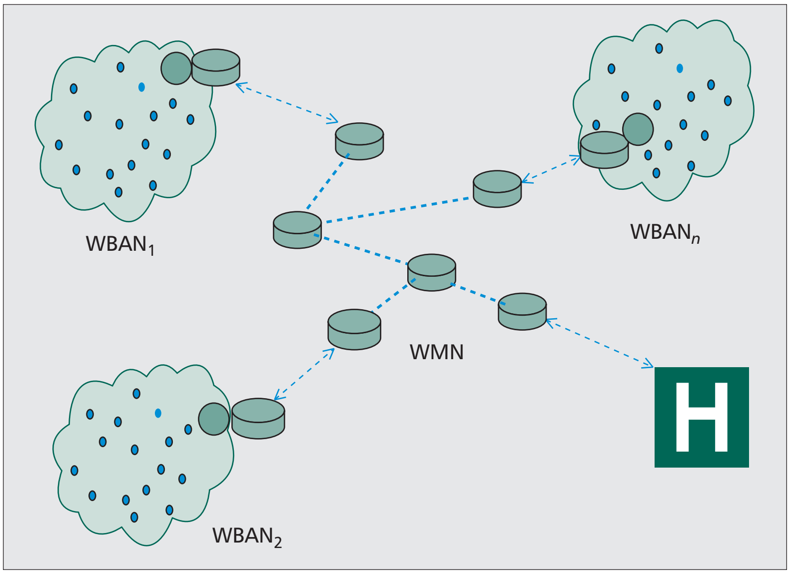

Figure 1. Healthcare System Scenario: A WBANi is a cluster i-th composed of POC nodes attached to patients that communicate vital signs to the clustersink node; a WMN supports the communication between the cluster-sink and the remote hospital terminal.

	ZigBee	WiFi
Path loss exponent	3	3
Sink/WiFi Router Transmission Power	0 dbm	20 dbm
Sink capacity	30 pkt/s	—
Sensor Transmission Power	–3 dbm	—
Receiver signal threshold	–48 dbm	–48 dbm
Sensor Buffer Size	30	—
Sink/WiFi Router Buffer Size	300	500
Retry Limit	3	3
Ack timeout	0.000864 s	0.000864 s
Packet size	150 byte	2.5 Mbytes
Data rate	b/s	10 Mb/s

Table 1. ZigBee and WiFi protocol main parameters.

ing healthcare delivery because it gives a variable management of the POC devices depending on the priority of the data carried. Moreover, it improves the management of vital signs in differentiated scenario conditions such as normal, on-demand and life-critical applications in which the packets carrying the information of a dying patient need to reach their destinations on time. From the technological point of view, the algorithm is implemented in the transport layer of the traditional network stack model, and is designed to work with any MAC protocol in the data-link layer with only minor modifications.

The rest of the article is organized as follows. The evaluation environment is described in terms of the healthcare network topology, communication protocols, performance metrics and vital signals, while a simulation analysis of the congestion effect on healthcare system performance is shown. Next, a sink proportional allocation strategy is proposed and validated by simulations. A congestion control based on an adaptive fairness criterion is presented to deal with differentiated and dynamic scenarios. Finally, the conclusions are outlined.

Healthcare System Simulation and Evaluation Environment

Most healthcare system scenarios are composed of a cluster of WBANs relaying vital information to a hospital (H) by a WMN as shown in Fig. 1. Each WBAN is characterized by many-to-one traffic patterns with a single sink/router node receiving information from the POC sensors affixed to one or more patients in the sink hearing area. In this article, we will focus our attention on such a representative healthcare topology scenario in which all the POC sensor nodes are stationary and transmit data to the hospital terminal (H) by a sink terminal data collector. Generally, a sink is a node with a high processing capability that helps to transmit the received packets from the POC sensors or WBAN relay nodes towards their destination. Depending on the application, a sink is a device such as a PDA, laptop, cell phone, wrist watch, headset, or even robot. The communication between the sinks and the hospital terminal is guaranteed by a wireless mesh network. This results in a heterogeneous wireless communication network as it is composed of devices adopting different protocols such as Zigbee and WiFi. In this article we describe an evaluation environment which we have set up in a Matlab/Simulink-based simulator TrueTime [12], which facilitates the co-simulation of controller task execution in real-time kernels and in a wireless network environment. The simulations are performed using the above topology of sensors randomly transmitting their information to the sink. The intra BAN protocol used for the POC-Sink communication is the standard Zigbee, while the protocol of the WMN supporting sink-remote hospital terminal communication is WiFi 802.11. Notice that the considered scenario is representative of a probably heterogeneous network scenario due to the wide diffusion of both the standard Zigbee protocol for low power POC sensors and WiFi 802.11 supporting city telecommunication (e.g. the Smart City concept). Moreover, the methodology of the proposed control takes in different scenarios of heterogeneous network technologies such as bluetooth or wired backbone. For this reason, we have built the simulation environment to include the following models:

1 The intra WBAN standard protocol Zigbee used for POC sensor-sink communication
2 The wireless mesh protocol WiFi 802.11 supporting sink-remote hospital terminal communication
3 The Ad-hoc On-Demand Distance Vector Routing Protocol (AODV) to route packets in the network
4 Models of the main vital signs, such as respiration, electrocardiogram, fetal electrocardiogram, and oxygen saturation of a pacemaker/defibrillator control system device.

In addition, the simulation model takes the path-loss of the radio signals into account.

The radio model includes support for

- Ad-hoc wireless networks
- Isotropic antennas
- Any inability to send and receive messages at the same time
- The path loss of radio signals modeled as $1/d^\beta$ where d is the distance and β is a parameter chosen to model the environment in [4, 5]
- Interference from other terminals, depending on the relative node distance and related power transmission.

In the following section we will present the vital signs model and the main performance metrics considered in the article. For additional information about the WiFi (802.11b/g), Zigbee (802.15.4) and AODV protocols we refer the interested reader to the references [1] and simulator manual [12]. In Table 1 the protocol parameters used in the simulation environment are summarized. Notice that we have considered the AODV protocol as representative of a common routing protocol adopted in the literature also for healthcare applications ([13]). Different works show how AODV outperforms other protocols such as DSLR (e.g.. [14]) in terms of time delivery and throughput. Finally, AODV presents good performance when the number of sensors is varying and in the presence of a mobile node which is a characteristic scenario of a healthcare application. In the following subsection, we consider the healthcare network performance under varying numbers of nodes as well as in the presence of a mobile POC sensor to show the effectiveness of the proposed approach coupled with the AODV protocol functionality. As the proposed strategy is actually a flow control without leveraging on the routing operation, the general performance trends obtained in the case of the AODV protocol should hold in the case of different routing protocols. Anyway, the advantages and drawbacks of the specific protocol may affect the overall healthcare performance: for instance, from the above consideration, in the case of a mobile node it is better to consider the AODV protocol than that of the DSLR.

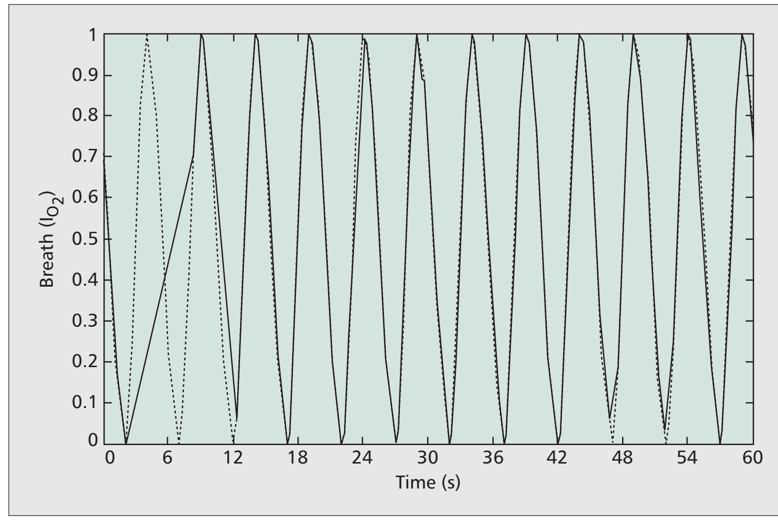

Figure 2. Proportional fair congestion control: Breathing vital signal received at the hospital (continuous line), Breathing vital signal sampled at the POC sensor (dashed line).

Vital Signs Model Simulation

In the following sections we will describe the main vital signs implemented in the simulator following the model given in the original references.

Respiration — Respiration is an important physiological function that quantifies the physiological states by volume, timing and shape of the respiratory wave form. It is associated with the kinematics of the chest thereby bringing about changes in the thoracic volume. Among sensors used to measure respiration, recently, a wearable based piezo-resistive sensor has been developed [15]. This signal requires a reporting rate ranging from 10Hz to 50Hz [1]. An example of a breath signal implemented in the simulator is shown in Fig. 2 (dashed line), for a sampling time of 0.1 s. Examples of applications include reliable respiration monitoring to detect respiratory depression and airway obstruction in post-surgical patients, diagnosis and treatment for obstructive sleep apnea, and the detection of Sudden Infant Death Syndrome (SIDS).

Electrocardiogram — The electrocardiogram (ECG) is a time-varying signal reflecting the ionic current flow which causes the cardiac fibers to contract and subsequently relax. The ECG surface is obtained by recording the potential difference between two electrodes placed on the surface of the skin. In this context, for simulation purposes, we have used a dynamic model proposed in the literature [16], based on three coupled ordinary differential equations which are capable of generating realistic synthetic electrocardiogram (ECG) signals. Standard clinical ECG applications can require a reporting rate from 200Hz to 300Hz [1]. In Fig. 3 (dashed line) the dynamics of an ECG signal implemented in the proposed simulator by using the above model is shown , when the sensor sampling time is 3 ms. The scenario is representative of a diagnosis of heart disease, an ambulatory care clinic health monitoring, a waiting room, and the monitoring of the alertness level of the driver.

Fetal Electrocardiogram — In recent years, Fetal Heart Rate (FHR) analysis has become a widely accepted means of monitoring fetal status. The fetal ECG is an electrical signal that can be obtained non-invasively by applying a pair of electrodes to the abdomen of a pregnant woman [17]. The characteristics of the FECG, such as the presence of a signal, and its rate, wave form and dynamic behavior are useful in determining the fetal life and maturity and the existence of fetal distress or congenital heart disease. Standard clinical FECG applications can require a reporting rate close to 200 Hz [1]. In Fig. 4 (dashed line) the dynamic evolution of the Fetal Cardiac Frequency vital sign (in the following briefly FCF) is shown with the sampling time fixed to 4 ms. Environmental scenarios include clinical assistance during labor, and telemedicine.

Pacemaker and Implantable Defibrillator Devices — An implanted defibrillator is a device that prevents death from a cardiac arrest. It shocks the heart, if it needs to be shocked, if there is any life-threatening rhythm disturbance from the lower chambers of the heart. Because it has a pacemaker built into it, a defibrillator also has the capability of stimulating the heart like a pacemaker, to help stop excessively fast rhythms, at times, and to prevent the heart from beating too slowly. Conventional pacemakers/defibrillators sense specific peaks in the electrocardiograph signal and may pace either the ventricle only or pace the atrium and then the ventricle following a time delay. In past years, it has been considered that oxygen saturation SO_2 in the venous blood appears to be the only practical controlled variable for rate-responsive pacing and patient monitoring after the establishment of a ROSC state (Return Of Spontaneous Circulation). The oxygen saturation SO_2 in the venous blood, commonly referred to as sats, measures the percentage of hemoglobin binding sites in the bloodstream occupied by oxygen. At low partial pressures of oxygen, most of the hemoglobin is deoxygenated. The SO_2 sensor uses reflection oximetry to measure the oxygen saturation in the central venous blood. The SO_2

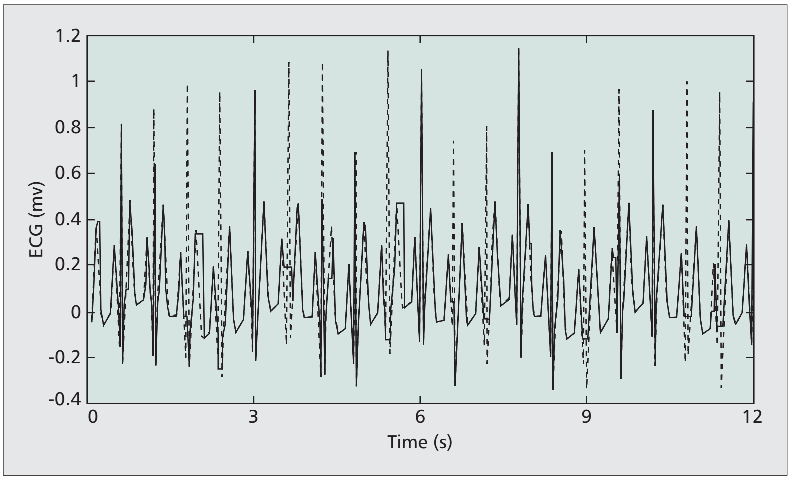

Figure 3. Uncontrolled case: ECG signal received at the hospital (solid line). ECG vital signal sampled at the POC sensor (dashed line).

signal is the input to a defibrillator/pacemaker program control unit which determines the appropriate pacing frequency. A pulse generator is used to shape the voltage pulse at the electrode in the right ventricle. Using this closed-loop system, patients have demonstrated an improvement in exercise tolerance. This system has been investigated using an experimental data based non-linear model of the pacemaker-cardiovascular system in [18]. The SO_2 level in the venous blood is fed back to the pacemaker and compared with a reference SO_2 level fixed to 0.12 liters of oxygen (l_{O2}) per liter of blood (l_{blood}). The difference is multiplied by the pacemaker controller gain and added to a minimum value to give the pacing rate. In [19] a root locus approach to analysis was described, modeling and designing the pacemaker-cardiovascular system. We have implemented in the simulation environment the closed loop model following the suggestions exploited in [19]. In Fig. 5 (dashed line) the dynamics of a SO_2 control system is shown dealing with patient activities and guaranteeing set point regulation. The sampling time is 3 ms and the applicative scenarios include telemedicine, and healthcare in the waiting room.

Performance Metrics

Depending on the type of target application, QoS in healthcare systems can be characterized by, among other factors, reliability, energy efficiency, timeliness, robustness, availability, and security. Among the different performance indices measuring the level of QoS, the following are particularly significant and have been evaluated in the evaluation environment discussed above:

- Delay is the time elapsing from the departure of a data packet from the source node to its arrival at the destination node, including queuing delay, switching delay and propagation delay, etc. Delay sensitive applications are common in healthcare environments in order to fulfill specific real-time requirements such as the timely access to diagnostic information (e.g.. ECG, FECG) and fast control operations (e.g. defibrillator shock, insulin inhalation);
- Reliability is the packet reception ratio (the number of received packets divided by the number of "transmitted" packets);
- Energy consumption is the energy spent in the time to permit the network to work. The nodes must be capable of playing their role for a sufficiently long period using the energy provided by their battery. Consequently, energy efficiency is one of the main requirements of a WBAN. Packet collision at the MAC layer, routing overheads, packet loss, and packet retransmission reduce energy efficiency. Notice that energy consumption strongly affects sensor network performance indicators such as the system lifetime (the duration of time until some node depletes all its energy) and the network coverage (this means that the entire network space can be monitored by the sensor nodes);
- Scalability is the ability of the healthcare system to guarantee an acceptable performance (i.e. a reliability >80 percent) with the increasing number of patient sensors. It indicates if the healthcare system will be suitable for a large nursing system.

Evaluation of Congestion Effect on Healthcare Delivery System Performance

First, we have analyzed, by using the simulator exploited above, the effect of congestion phenomena on the healthcare network performance. We have considered the representative many-to-one scenario with a single router-sink node collecting data received from the WBAN devices in the sink hearing area. The WMN is composed of two additional sinks sending background traffic to the hospital terminal. For each signal at each POC sensor, we have appropriately packaged the sampled piece of vital sign information into a packet to be sent to the sink. The average intra-WBAN distance was 10m, while the average intra-WMN distance was 50m. We have evaluated the network reliability and scalability by increasing the number of the POC sensors accessing the router-sink from 3 to 12 (and so the overall sink input reporting rate is increased). As we note from Fig. 6 (dashed line), there is a threshold of 30 pkt/s for the overall POC sensor reporting rate that produces network congestion with a reduction of reliability and scalability, and an increase of packet loss: this threshold corresponds to the capacity C=30 pkt/s of the sink to manage packets.

The worsening of the performance in terms of reliability is mainly due to the buffer overflow and collision packet losses. On the other hand, the time delay for the delivered packets is due to the time each packet spent waiting in the sink queue before being transmitted to the hospital. Increasing the value of the input reporting rate will lead to a collapse of the sink with a heavy reduction in reliability and time delivery performances due to the increase of packet losses, packet retransmission and collision effects. In Fig. 8 the average energy consumed by the nodes as a function of the overall input rate at the sink (e.g. with an increasing number of sensors transmitting information) is shown . In this case the increase of packet losses and packets retransmitted due to congestion and collision phenomena in turn increases the energy spent by the POC sensors, with a consequent heavy reduction in network life time and network coverage. The main effect of the congestion at the sink bottleneck node on the healthcare delivery system performance is the reduction of the quality of the vital signs received at the hospital. This makes it hard to reassemble the vital signs at the hospital server and therefore makes any estimation of the patient's pathology by the doctor more difficult . Indeed, an increase in the reporting rate and therefore of the traffic in the network leads to a worsening of the quality of the vital signs, even at the high priority, which requires more bandwidth as is shown in Fig. 3 for the case of the ECG signal. On the other hand, the breathing signal presents a low degradation level although it requires a low priority and low bandwidth (Table 2). In a similar way, the vital signs FCF (Fig. 4) and SO_2 (Fig. 5) received at the hospital (dashed line) are more significantly deteriorated than the original POC signals (continuous line). Therefore, the shape of the signals with a high bandwidth requirement can strongly deteriorate, losing significant data for a correct patient diagnosis. For instance, the effect of congestion on the quality of the ECG is the loss of many peaks (e.g. note in Fig. 3 the original signal (dashed line) compared with the signal received at the hospital (solid line)) that is of critical importance for a correct diagnosis of the patient's cardiac pathologies (e.g. ventricular tachycardia, and ventricular fibrillation). Moreover, in Table 2 (the uncontrolled case) the average latency under sink congestion conditions is shown (e.g. the overall reporting rate is fixed at 32 pkt/s). In this case the delivery time is the same irrespective of both the different bandwidth/priority requirement of the vital signs (e.g. defibrillator and ECG signals require more responsiveness than the respiration signal) and the upcoming emergency operation (e.g. a cardiac arrest requiring a responsive defibrillator shock). We can observe that also for a low reporting rate, packet loss might occur due to MAC error and/or collision. For instance, in this case, the overall packet loss due to the collision effect is about 24 percent as shown in Table 2.

Signal/Priority	Uncontrolled case	Controlled case
Breath/1	40 s	60 s
FECG/5	40 s	2 s
SO2/5	40 s	2 s
ECG/10	40 s	0.5 s
Defibrillator/10	40 s	0.5 s
Packet Collision loss	24%	20%

Table 2. Time delivery access of vital sign diagnostic information of different priorities.

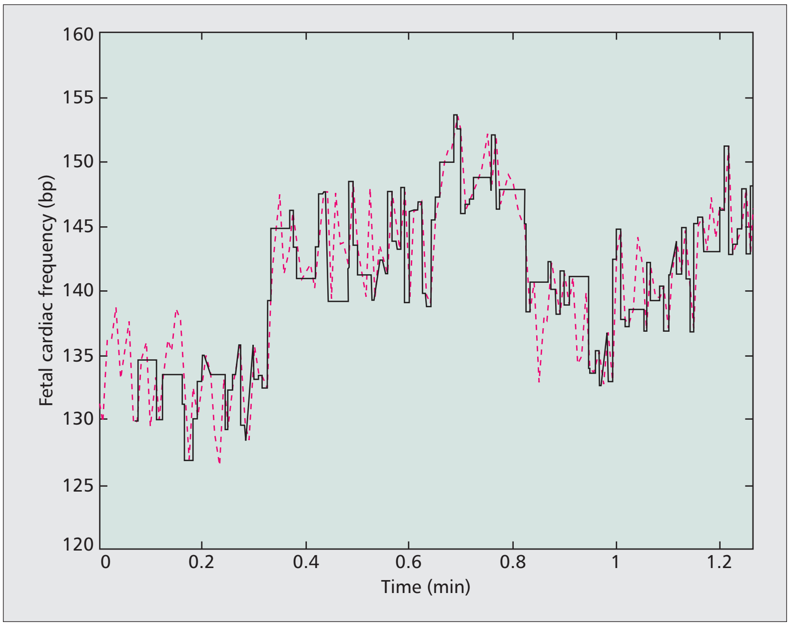

Figure 4. Uncontrolled case: FCF signal received at the hospital (continuous line), FCF vital signal sampled at the POC sensor (dashed line).

Weighted and Adaptive Fairness Criteria for Congestion Control

The main idea is to allocate sink bandwidth resources C, fulfilling the requirement that the total capacity made available to the sensors is less than or equal to C. Namely, for a given number n of POC sensors and a fixed set of priorities $\mathbf{p} = (p_1, \ldots, p_n)'$, the congestion control at the sink allocates an amount of capacity to the j-th sensor, r_j, so that:

$$r_j = \frac{\sqrt[\alpha]{p_j}}{\sum_{k=1}^{n} \sqrt[\alpha]{p_k}} C \tag{1}$$

with p_j being the weight associated to the sensors $j - th$ and α a tunable parameter affecting the fairness property ([20]) of the allocation vector $\mathbf{r} = (r_1, \ldots, r_n)'$. We have proposed the rate control law (Eq. 1) that corresponds to the maximization of the sum of the same parametric concave utility function, namely $\Sigma_{j=1}^{n} U(\alpha, r_j, p_j)$ with

$$U(\alpha, r_j, p_j) = \begin{cases} p_j r_j^{1-\alpha}(1-\alpha), & \alpha \neq 1; \\ p_j \log(r_j), & \alpha = 1. \end{cases}$$

subject to the constraint $\Sigma_{j=1}^{n} \leq C$ over $\mathbf{r} \geq 0$ ([20]). There are different solution states for different values of α. In particular, for α = 1 a proportional fairness allocation is obtained while it converges to the Max Min Fair one for α tending to infinity. The allocation of the available resources among the POC sensors according to Eq. 1 guarantees not only that the allocated capacity is within the accepted levels avoiding congestion but also that the allocation follows some fairness criteria. Specifically, with proportional fairness, POC signals with greater weights p_j are allocated a larger amount of capacity. Thus, Eq. 1 can be used by the sink resource manager to govern the relative fair allocation of capacity among POC sensor signals based on their priorities. In the other extreme, in the cases of equal $\mathbf{p}$ components or high values of α,

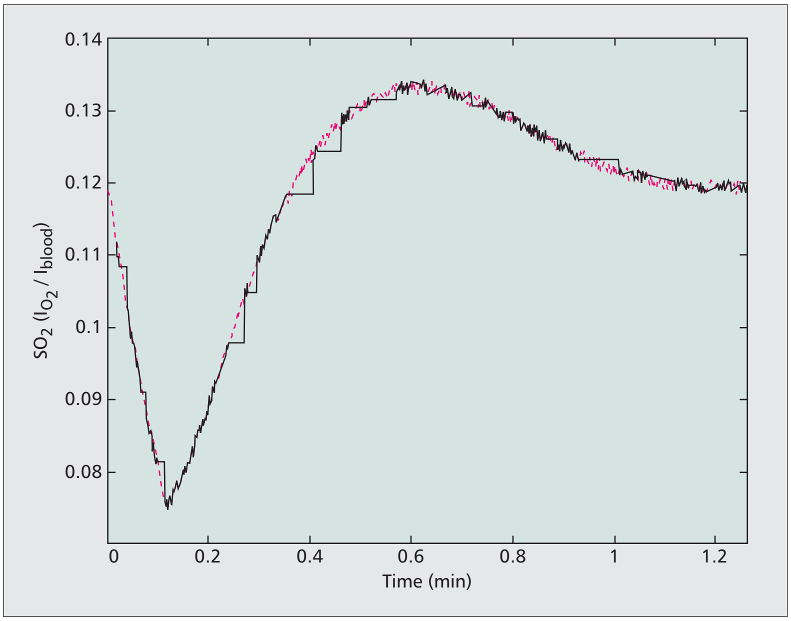

Figure 5. Uncontrolled case: SO_2 vital signal received at the hospital (continuous line), SO_2 vital signal sampled at the POC sensor (dashed line).

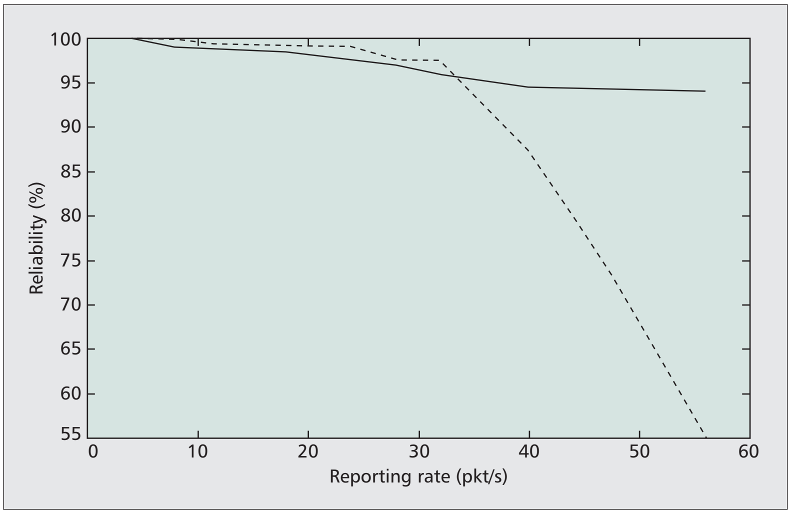

Figure 6. Health care remote system reliability as a function of the POC sensor reporting rate: uncontrolled case (dashed line); controlled case (solid line).

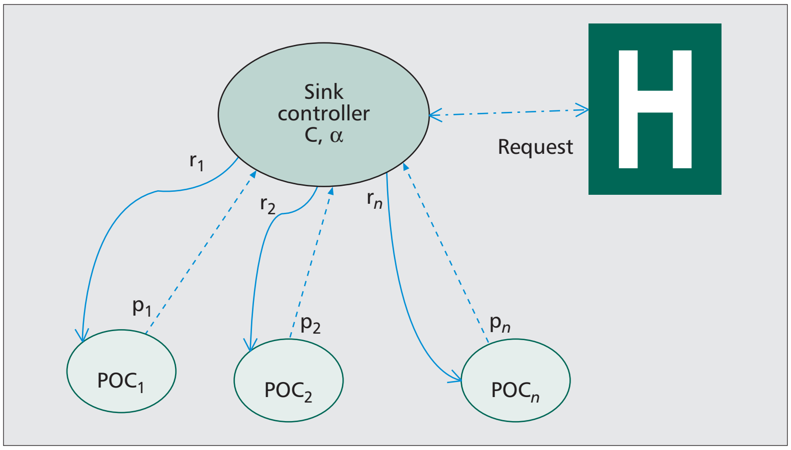

Figure 7. The proposed controller scheme.

the resulting resource allocation is Max-Min Fair with the same quota of resource C/n allocated to each sensor. We show in Fig. 9 the allocated sink capacity $C = 30$ pkt/s to 10 POC sensors divided into three classes $\mathbf{C}_1 = \{\text{Gold}\}$, $\mathbf{C}_2 = \{\text{Silver}\}$, and $\mathbf{C}_3 = \{\text{Bronze}\}$ with decreasing priorities of 10, 5 and 1, respectively. The basic priority values of the vital signals are given according to the medical and network constraints, but they can dynamically vary due to specific doctor/patient purposes (as will be shown later). For example, in the case of Table 2 the priority is assigned to the signal according to the degree of timeliness required by the associated healthcare service. Namely, letting τ_{C_i} the time delivery desired for a signal class be C_i, $i = 1, 2, 3$, we would obtain the following inequality:

$$\tau_{C_1} \leq \frac{\tau_{C_2}}{2} \text{ and } \tau_{C_2} \leq \frac{\tau_{C_3}}{5}.$$

Therefore, one possible assignment for the priorities is 10, 5 and 1, respectively, for the classes C_1, C_2 and C_3. As will be validated later, the resulting time delivery under the proposed controller satisfies the above inequality (e.g. the controlled case in Table 2). In general, different assignments can be performed depending on the specific requirements. From Fig. 9 we note that for a low value of α, the resulting allocation is proportional fair with a POC signal class at a greater priority p_j receiving a larger amount of capacity. For increasing values of α, the resulting resource allocation is Max-Min Fair with the same quota of resource C/n allocated to each sensor.

A remote healthcare monitoring system is usually asked to cope with the following three kinds of scenario: normal, on-demand, and emergency. The first kind is related to the normal/standard network and the patient's condition (e.g. the health monitoring and treatment of a patient). The second is initiated by the doctor to acquire certain information, mostly for the purpose of diagnostic recommendations or a more accurate analysis. The emergency or critical scenario is usually initiated by the nodes when they exceed a predefined threshold and need to be accommodated in a short time. The latter two scenarios are totally unpredictable. Therefore, the healthcare monitoring scenario is characterized by dynamic high network heterogeneous traffic types (different sensors with different samplings) and differentiated service requirements that make QoS support more complex and challenging than the standard (less vital sign sensitive) network applications. In order to deal with these healthcare networks, we have extended the proposed approach into an adaptive fair congestion control scheme that is different from the existing mechanisms proposed in the literature.

In Fig. 7 the proposed scheme is shown. Specifically, we consider a network module controller located at the Sink that is designed taking into account the analysis carried out above and the formula 1. The Sink is characterized by the link capacity C, while α is the controller parameter. The sink controller receives information on the priority (e.g. **p**) of the POC sensors and allocates to them the rate vector **r** in order to fulfill the constraint on the link capacity. Additionally the controller parameter α is fixed according to the different type of required fairness allocation. The value of α may be tuned also taking into account of specific request from the Hospital remote terminal. Additionally the enabled POC sensors may adapt their priority on the base of a specific situation. Therefore the Sink controller changes the allocated capacity on the base of POC priority, the desired level of fairness and specific request from the Hospital. In this way the controller is adaptive to different scenarios described above (as it will be detailed later), bidirectional (e.g. it copes with requirements from the coordinator/doctor to the patient and vice versa), and simple to implement. It can therefore guarantee timeliness in service delivery.

The controller algorithm has been implemented by a network module at the transport layer of the traditional network stack model. Specifically, the available field of protocol control packets has been simulated to send priority and controller information between the sink/remote station and the POC sensors. A library has been built extending the TrueTime simulator with new application components which are in charge of data treatment and a new agent has been added to allow the simulation of data transfer. The library has been designed to extract POC priority information and to set the bandwidth allocation according to Eq. 1 and the scheme in Fig. 7. This simulates at the transport level the possibility of communicating priority and control information among the POC sensors, sinks and the hospital terminal that may be implemented at a lower level in a different way depending on which technology is considered.

In the following section, we first present a proportional fair allocation to cope with nominal differentiated services associated with different signal priorities and validate it in a mobile scenarioo. Next, we introduce an adaptive fair allocation and congestion avoidance strategy to deal with dynamic and differentiated healthcare service delivery. The example also highlights the different possible ways to tune the control algorithm parameters.

Proportional Fair Allocation

In this subsection, we consider the scenario introduced earlier, and assign to the couples (defibrillator, ECG), (FCF and SO_2) and to the breathing vital sign respectively the three above priority classes C_1, C_2 and C_3. The class priority is assigned according to the requirement introduced above. Specifically, we consider three signals of class C_1 (i.e. ECG, defibrillator) at priority $p_i = 10$, $i = 1, \ldots, 3$, four signals of class C_2 (i.e. FECG, SO_2) at priority $p_i = 5$, $i = 4,..,7$, and three signals of class C_3 at priority $p_i = 1$, i $= 8, \ldots, 10$. The controller parameter is fixed at $\alpha = 1$ (proportional fair allocation). In this way, by applying the strategy allocation in Eq. 1 based on the scheme described in Fig. 7, the link capacity quota allocated by the Sink controller to each signal of the class C_1 is

$$r_j = \frac{p_j}{\sum_{k=1}^{10} p_k}$$
$$= 10/(3*10+4*5+3*1) = 10/53, j = 1,2,3.$$

Similarly, the capacity quota allocated to each signal of the classes C_2 and C_3 is respectively 5/53 and 1/53. We note in Fig. 6 (solid line), the effectiveness of the allocation strategy in improving healthcare system reliability and scalability compared with the uncontrolled case. Indeed, in the uncontrolled case when the number of POC sensors increases from 3 to 12, the overall transmission rate increases until it saturates the link capacity (this happens for the overall POC sensor rate of about 30pkt/s, the link capacity value). This causes an uncontrolled increase of the sink queue with a buffer overflow, which in turn causes a packet loss and a related heavy reduction of network reliability. On the other hand, in the case of the proportional fair controller, the rate of the POC sensor is controlled and allocated so as to fulfill the link capacity constraint and therefore avoid buffer overflow. This increases the network scalability, as the network is able to manage the mode POC sensors. When the number is

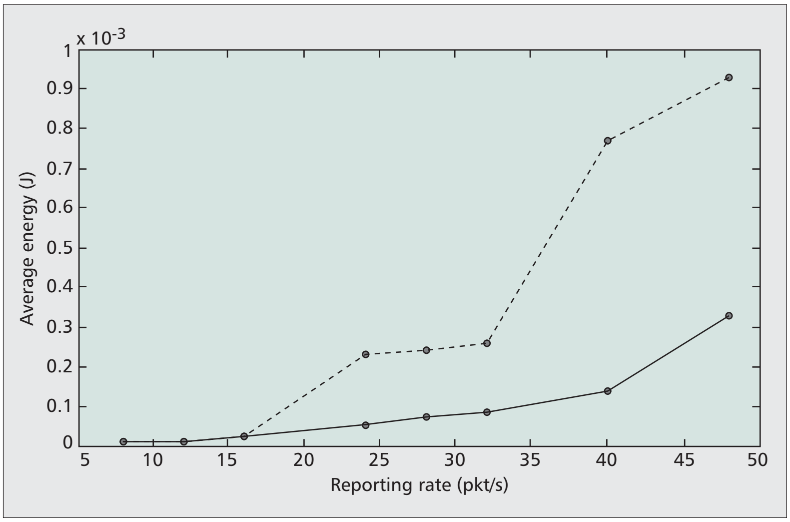

Figure 8. The average energy consumption of the POC sensors as a function of the reporting rate: the controlled case (solid line), and the uncontrolled case (dashed line).

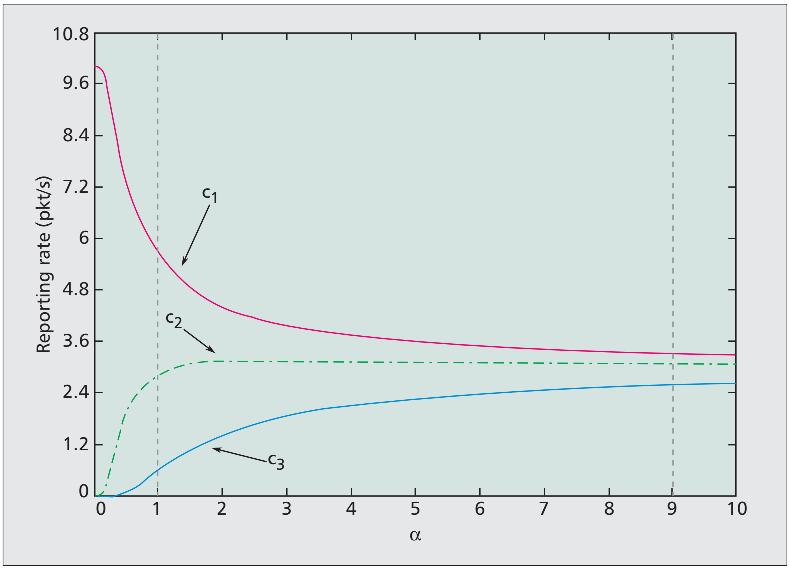

Figure 9. Sink capacity allocation to three classes C_1, C_2 and C_3 with decreasing priority for $n = 10$, $C = 30$ pkt/s.

really high, there is an effect of packet collision that slightly reduces the reliability.

Additionally, the energy and time delivery performances are strongly improved as shown respectively in Fig. 8 and Table 2 (the controlled case). In particular, the time delivery in a sink congested scenario is proportional to the signal priority satisfying the requirement in terms of the class time delivery. Specifically, the time delivery of the ECG signal or defibrillator alert is much lower than that of the respiration signal. This results in a correct extraction of the vital signal information at the hospital remote terminal for the ECG signal as depicted in Fig. 10. Similarly, the signals of the class C_2 (e.g. FCF in Fig. 11, SO_2 in Fig. 12) as well as that of class C_3 (e.g. breathing in Fig. 2) are correctly received at the hospital (continuous line) compared with the original signals transmitted (dashed line).

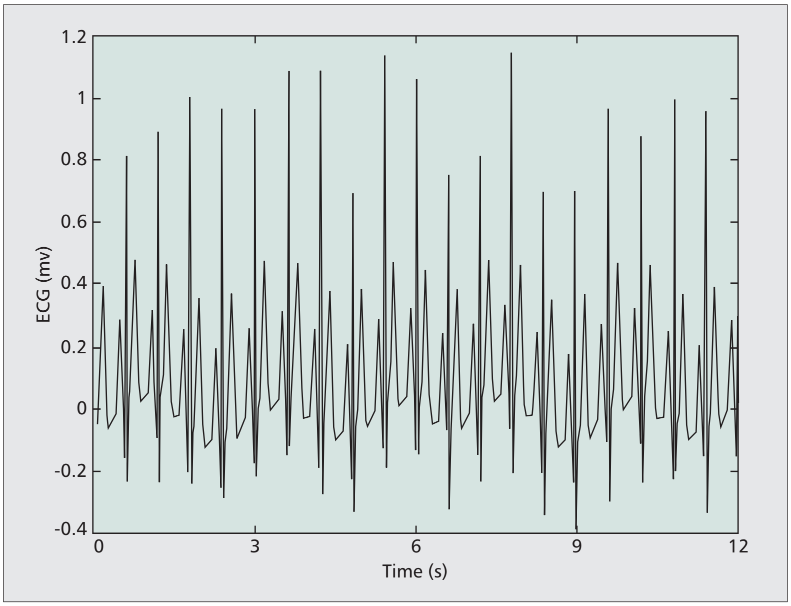

Figure 10. Proportional fair congestion control: ECG vital signal received at the Hospital.

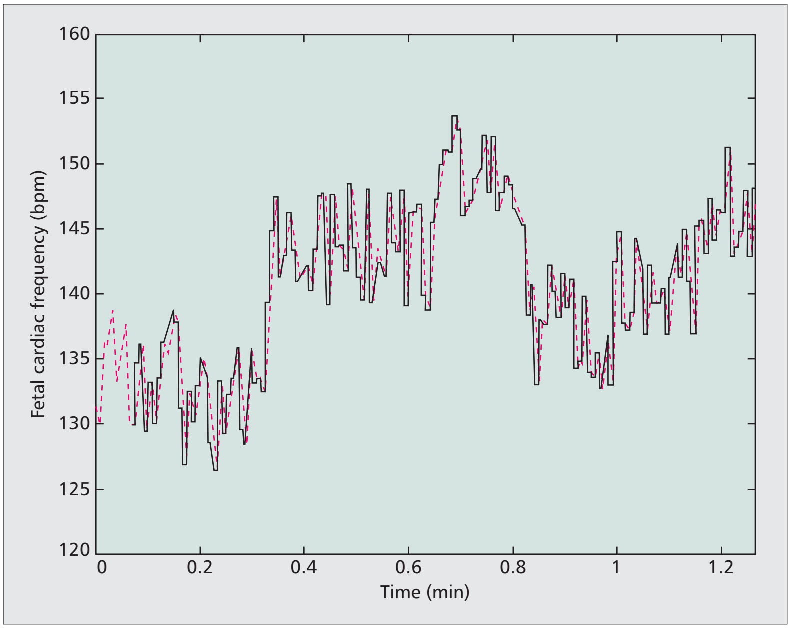

Figure 11. Proportional fair congestion control: FCF vital signal received at the Hospital (continues line), FCF vital signal sampled at the POC sensor (dashed line).

Mobile Scenario

In order to assess the effectiveness of the proposed congestion control approach supported by the AODV protocol, we have considered the scenario of a mobile node transmitting high priority traffic to the hospital. We report in Fig. 13 the reliability for different node speeds varying from 1 meter per second (i.e. walking speed) to 30 meters per second (i.e. ambulance speed). From the Fig. 13 we observe how the performance in the uncontrolled case has become worse compared with the controlled case (i.e. the proportional fair allocation) under increasing speeds. Indeed, the mobile node transmits information at a high rate and priority and causes local congestion to the sinks with which it is connected during the motion. Therefore, in the case of the uncontrolled scenario the traffic is not controlled proportionally to the required bandwidth and causes local congestion with a worsening of the overall network reliability. On the other hand, the proportional fair controller allocates the bandwidth proportionally to the priority so avoiding congestion. Notice how the AODV is effective in supporting the healthcare mobile network scenario.

Adaptive Fair Allocation for Dynamic Healthcare Scenario Management

In this subsection, we present an adaptive fair allocation approach to deal with differentiated scenarios. Additionally, the different tuning possibilities of the proposed algorithm at the different tier levels of the network are outlined. To make an illustrative example, we consider 8 POC sensors divided into three priority classes, C_1 (3 sensors), C_2 (4 sensors) and C_3 (1 sensor) accessing a sink of capacity $C = 30$ pkt/s. The *terminal node manager* (sink and remote station) as well as *the local POC controller* may be interested in seeking a compromise between the two extreme fairness approaches (proportional and max-min) generating various allocations depending on the congestion, the scenario (i.e. critical or normal), and the priority/requirement of the POC device. To summarize, we briefly describe four possible application scenarios in which there is a dynamic adaptation of the parameters affecting the fairness of the allocated resource **r**. Specifically, Fig. 14 shows the allocated capacity of each class for the following four representative scenarios:

Nominal scenario: For $t \in [0, 1.5)$ min, the system works according to the nominal condition setting in terms of the patient's signal priority and fairness. The sink controller allocates the rates r_i shown in Fig. 14 according to the proportional fair strategy described earlier and implemented by the scheme in Fig. 7, with $\alpha = 1$ and vector priority $\mathbf{p} = (10, 10, 10, 5, 5, 5, 5, 1)$ provided by the POC sensors;

On-Demand scenario: At the remote terminal (i.e. the hospital) doctors detect a particular critical condition for a specific vital signal (i.e. the ECG) and so ask to the sink more information for diagnosis purposes (by a Request in Fig. 7). In Fig. 14 for $t \in [1.5, 2.5)$ min, the sink control decreases α to allocate more bandwidth to the ECG signal. The value of α is selected from a look-up table. The table is built by carrying out a preliminary analysis similar to that shown in Fig. 9 and using the Eq. 1 in order to define the value of α to assess a specific capacity allocation for each signal of a class, C_1, C_2 or C_3. In this example, a pre-designed α value of 0.6 has been selected from the table in order to allocate a capacity quota of about 7 pkt/s to each signal of the highest priority class C_1 (Fig. 9);

Critical scenario: Locally, at the POC device, a specific critical condition is detected (i.e. in the disaster or emergency scenarios) so that it needs more bandwidth. Therefore, the enabled local POC controller increases its priority and sends it to the sink controller (as shown in the scheme in Fig. 7). The allowed priority values are within the range of priority defined according to the medical/network indications. In Fig. 14 for $t \in [2.5, 3.5)$ min, the priority of the class at the lowest value (i.e. priority 1) rises to that of the highest class priority (i.e. priority 10), receiving the same amount of bandwidth allocation at $t = 3.5$ min;

Faulty scenario: In the case of any fault of the healthcare system components, the remote station controller (Hospital/Sink) adjusts or requires the α to apply a Max-Min Fair allocation strategy and assure an equal share among all POC devices. In Fig. 14 for $t \in [3.5, 5]$ min the Max-Min Fair allocation is assessed by setting $\alpha = 10$ with the almost equal allocated bandwidth at $t = 5$ min.

Overall, notice that in all the above scenarios the bandwidth allocated to the POC devices satisfies the capacity constraint $\Sigma_{j=1}^{n} r_j \leq C$ and so congestion is avoided.

Finally, in Table 3 the performance in terms of reliability and time delivery per class in the cases of uncontrolled, proportional fair and adaptive fair allocations are reported for each of the above scenarios, 1), 2), 3) and 4). Notice that the performances of the adaptive and proportional fair scheme are the same in scenarios 1) and 3) because the adaptive scheme acts as a proportional fair one. Differently, the scenarios 2) and 4) can only be well managed by the adaptive scheme because it can control the α parameter in order to efficiently allocate the capacity differently from the uncontrolled and proportional fair cases. Overall, the proportional and adaptive schemes outperform the performance of the uncontrolled case. Finally, the adaptive scheme can deal with the additional scenarios 2) and 4) allowing the network management by the remote terminal controller (at the sink or at the hospital base station) in order to request more patient information and assure a minimal acceptable quality of the vital sign monitoring service in the presence of faults.

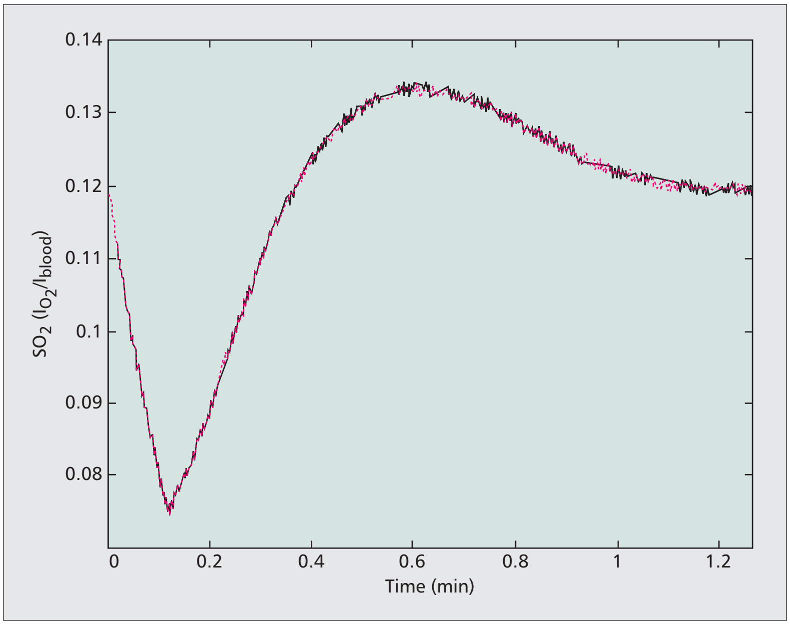

Figure 12. Proportional fair congestion control: SO_2 vital signal received at the Hospital (continues line), SO_2 vital signal sampled at the POC sensor (dashed line).

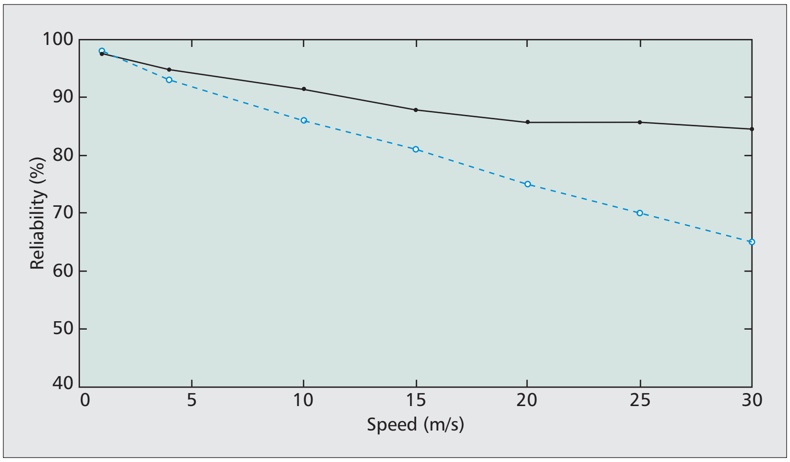

Figure 13. Reliability in mobile scenario. Uncontrolled case (dashed line), proportional fair allocation (solid line).

Conclusions

Due to the many-to-one nature of the traffic patterns in modern healthcare wireless system architectures, congestion at the bottleneck node can occur when the POC node traffic increases compared to the node capacity. Therefore, it is a critical issue for healthcare applications to design an appropriate sink capacity allocation strategy addressing reliability and the timely access to diagnostic information without failure. We have built a realistic simulation environment for remote healthcare system evaluation including the main vital signs and wireless network protocol modeling. The simulator is used to analyze and evaluate the effect of congestion phenomena on the healthcare system performance in terms of reliability, timeliness and efficiency. Next, we have shown the effectiveness of adopting a proportional fairness control strategy at the sink in order to regulate the rate of flow of data at the POC nodes proportionally to their priority. An adaptive fair allocation has also been proposed to cope with the dynamic and differentiated scenarios characteristic of healthcare applications.

References

[1] Y. Zhang and T. A. Gulliver, "Quality of Service for Ad Hoc On-Demand Distance Vector Routing," *IEEE Int'l. Conf. Wireless and Mobile Computing*, vol. 3, 2005, pp. 192–96.

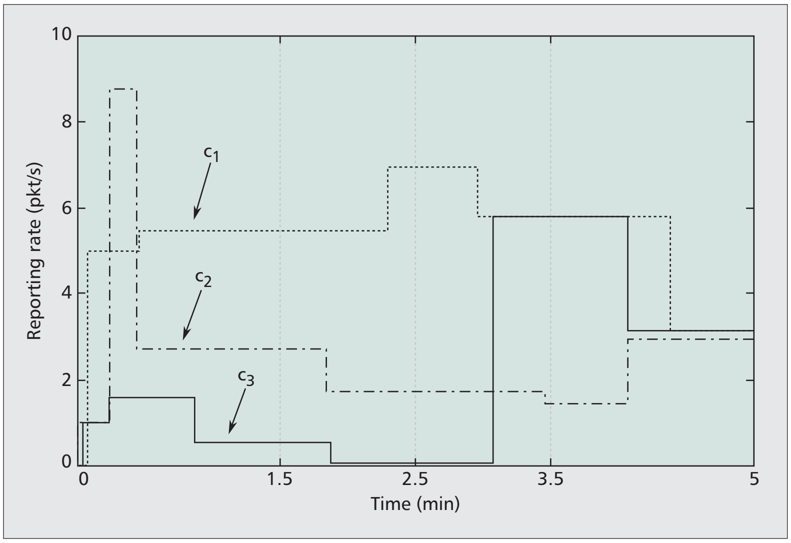

Figure 14. Adaptive Fairness criteria: capacity allocation to each POC sensor of the three class C_1, C_2 and C_3.

[2] A. P. Dhawan and B. C. Wheeler, "Emerging Technologies in Point-of- Care Health Care," *IEEE Trans. Biomedical Engineering*, vol. 58, no. 3, 2011.
[3] C. Lau *et al.*, "Asynchronous Web-based Patient-Centered Home Telemedicine System," *IEEE Trans. Biomedical Engineering,* vol. 49, no. 12, 2002, pp. 1452–62.
[4] A. Pietrabissa *et al.*, "Optimal Planning of Sensor Networks for Asset Tracking in Hospital Environments," *Decision Support Systems* (Elsevier, Great Britain), vol. 55, no. 1, Apr. 2013, ISSN 0167-9236, DOI: 10.1016/j.dss.2013.01.031, pp. 304–13.
[5] S. Misra, V. Tiwari, and M. Obaidat, "Lacas: Learning Automata-based Congestion Avoidance Scheme for Healthcare Wireless Sensor Networks," *IEEE JSAC*, vol. 27, no. 4, 2009, pp. 466–79.
[6] S. Misra, V. Tiwari, and M. Obaidat, "Improving QoS for ECG Data Transmission with Enhanced Admission Control in EDCA-Based WLANs," *IEEE Globecom*, 1–5, 2011.
[7] A. Zvikhachevskaya; G. Markarian, and L. Mihaylova, "Quality of Service Consideration for the Wireless Telemedicine and E-Health Services," *IEEE Wireless Commun. & Networking Conf.*, vol. 1–6, 2009.
[8] J. Mo and J. Walrand, "Fair End-to-End Window-based Congestion Control," *IEEE/ACM Trans. Net.*, vol. 8, no. 5, 2000, pp. 556–67.
[9] C. T. Huang *et al.*, "A Wearable Yarn-based Piezo-Resistive Sensor," *Sensors and Actuators A: Physical*, vol. 141, no. 2, Feb. 2008, pp. 396–403.
[10] M. Patel and J. Wang, "Applications, Challenges, and Prospective in Emerging Body Area Networking Technologies," *IEEE Wireless Commun.*, vol. 17, no. 1, Feb. 2010, pp. 80–88.
[11] S. Manfredi, "Decentralized Queue Balancing and Differentiated Service Scheme based on Cooperative Control Concept," *IEEE Trans. Industrial Informatics*, vol. 10, issue 1, DOI: 10.1109/TII.2013.2265879, ISSN :1551-3203, 2014, pp. 586–93.
[12] "IEEE 802.15 WPAN Task Group 6 (TG6) Body Area Networks," 2012.
[13] P. E. McSharry *et al.*, "A Dynamical Model for Generating Synthetic Electrocardiogram Signals," *IEEE Trans. Biomedical Engineering*, vol. 50, no. 3, 2003, pp. 289–94.
[14] G. K. Hung, "Application of the Root Locus Technique to the Closed-Loop SO2 Pacemaker-Cardiovascular System," *IEEE Trans. Biomedical Engineering*, vol. 37, no. 6, 1990.
[15] A. Boukerche, "Performance Evaluation of Routing Protocols for Ad Hoc Wireless Networks," *J. Mobile Networks and Applications*, vol. 9, no. 4, Springer, 2004.
[16] J. Seo Je*t al.*, "A Study on the Implementation of A Portable u-Healthcare System Using SNMP and AODV," *J. Mobile Networks and Applications, Conf. Proc. IEEE Eng. Med. Bio. Soc.*, 2007
[17] S. Manfredi, "A Theoretical Analysis of Multihop Consensus Algorithms for Wireless Networks: Tradeoff Among Reliability, Responsiveness and Delay Tolerance," *Ad Hoc Networks*, vol. 13, PART A, DOI Information: 10.1016/j.adhoc.2011.05.005, ISSN: 1570- 8705, 2014, pp. 234–44.
[18] S. Manfredi, "Design of A Multi-Hop Dynamic Consensus Algorithm over Wireless Sensor Networks," *Control Engineering Practice*, vol. 21, no. 4, DOI: dx.doi.org/10.1016/j.conengprac, 2012.12.001, 2013, pp. 381–94.
[19] G. F. Inbar *et al.*, "Development of A Closed-Loop Pacemaker Controller Regulating Mixed Venous Oxygen Saturation Level," *IEEE Trans. Biomedical Engineering*, vol. 35 1988, 679–90,.
[20] T. Solum, I. Ingermarsson, and A. Nygren, "The Accuracy of Abdominal ECG for Fetal Electronic Monitoring," *J. Perinatal Medicine*, vol. 8, no. 3, 1980, pp. 142–49.
[21] M. Ohlin, D. Henriksson, A. Anton Cervin, "TrueTime 1.5 Reference Manual," Department of Automatic Control, Lund University, 2007.

Biography

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Reliability [%] Time Delivery per Class τ_{C_i} [s], i = 1,2,3			
	Uncontrolled	**Proportional**	**Adaptive**
Nominal scenario	0.92 $\tau_{C_1} = 35, \tau_{C_2} = 35, \tau_{C_3} = 35$	0.96 $\tau_{C_1} = 0.4, \tau_{C_2} = 1.8, \tau_{C_3} = 58$	0.96 $\tau_{C_1} = 0.4, \tau_{C_2} = 1.8, \tau_{C_3} = 58$
On-demand scenario	—	—	0.95 $\tau_{C_1} = 0.2, \tau_{C_2} = 2.6, \tau_{C_3} = 70$
Critical scenario	0.75 $\tau_{C_1} = 45, \tau_{C_2} = 45, \tau_{C_3} = 40$	0.96 $\tau_{C_1} = 0.3, \tau_{C_2} = 2.8, \tau_{C_3} = 0.3$	0.96 $\tau_{C_1} = 0.3, \tau_{C_2} = 2.8, \tau_{C_3} = 0.3$
Faulty scenario	0.67 $\tau_{C_1} = 50, \tau_{C_2} = 80, \tau_{C_3} = 95$	0.88 $\tau_{C_1} = 3, \tau_{C_2} = 15, \tau_{C_3} = 7$	0.97 $\tau_{C_1} = 2, \tau_{C_2} = 2, \tau_{C_3} = 2$

Table 3. Reliability and time delivery under different scenarios (Nominal, On-Demand, Critical and Faulty) and allocation strategy (uncontrolled, proportional, adaptive).