

Joint Epidemic Control and Routing in Mass Gathering Areas using Body-to-Body Networks

Amira Meharouech*, Jocelyne Elias[†], and Ahmed Mehaoua*

Abstract—Body-to-Body Networks (BBNs) have recently gained momentum as a revolutionary technology for the monitoring of people behavior with real-time updates of medical records and interactive assistance in emergency situations, like the spread of pandemic diseases. This paper investigates the epidemic control issue in mass gathering areas (i.e., the airports) from a practical point of view by using BBNs and by adopting some key features from existing epidemiology models. We first introduce a BBN-based epidemic control framework. Second, we define an Epidemic-aware Routing Metric and then propose a Location-Aided Routing protocol tailored to BBNs, called BB-LAR, along with an epidemic control mechanism, in order to exchange epidemic data and help the authority control unit in detecting and quarantining the infected subjects. Finally, we evaluate the performance of BB-LAR with respect to existing routing schemes in terms of packet delivery ratio, end-to-end delay, and energy consumption.

Index Terms—Body-to-Body Network, epidemic control, routing.

I. INTRODUCTION

The huge penetration of Body-to-Body solutions for people behavior's monitoring and remote control in a wide range of markets is generating great social benefits. The BBN technology paves the way for new possibilities of ubiquitous health applications. In its simplest form, a BBN is a kind of ad hoc mobile network in which mobile nodes are wearable devices, either carried or worn by people [1], [2].

In this paper, we focus on the problem of preventing epidemic spread in mass gathering areas by using BBNs, especially where closer public contact makes easier the spread of pandemic diseases. We consider an airport indoor environment, where the authority control unit wants to ensure public safety and prevent the insurgence of pandemics inside the local population as well as the epidemic diffusion due to the migration of people across the countries. Indeed, recent studies name 40 airports most likely to spread diseases [3], [4]. Researchers used real traveler patterns, geographical information and airport waiting times to find out that these airports are disease-spread hot spots, and the most likely to facilitate the diffusion of a major pandemic from its origin. Some of those findings are reported in [3].

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The problem of spread of infectious diseases was initially investigated from a theoretical perspective; a lot of epidemic models have been developed and analyzed, and mathematical modeling of infectious disease spreading has been extensively studied for a long time. A comprehensive survey on these epidemic models can be found in [5], [6]. Yet, these studies suffer from some limitations: their inability to gather health data and social contact information simultaneously, namely in dynamic scenarios where the assumptions about human motions and social contacts are barely efficient.

In this paper, we investigate the problem from a more practical point of view, using the BBN technology and inspired by some ideas from epidemiology models, while keeping in mind their limitations for the studied challenging and dynamic scenario (i.e., the airport indoor environment). Indeed, the weaknesses of traditional approaches place BBN systems on the spotlight, due to their ability to ensure real-time health data sensing and support dynamic networks to control the face-to-face contact when mobile people can enter and leave the network randomly. More specifically, we introduce a novel BBN-based epidemic control framework, built upon a new routing protocol, in order to exchange epidemic data and help the authority control unit in detecting and quarantining the infected subjects. More in details, we first define an *epidemic threshold-based routing metric* and then propose a *Location-Aided Routing protocol for BBNs*, named *BB-LAR protocol*.

Furthermore, real-time interactions among Wireless Body Area Networks (WBANs¹), forming BBNs, allow each WBAN or person to choose an instantaneous defense strategy to ensure auto-preventive actions, even before quarantine strategies taken by the authorities.

Investigating routing issues goes parallel with energy efficiency, QoS and mobility considerations. Indeed, the information stream consists of short data packets that are passed from person to person (or WBAN to WBAN) and routed to the remote server (authorities). The other WBANs in the BBN all contribute a little with their energy and bandwidth to relay the packets. A BBN, like any sensor network, suffers limited energy resources, hence preserving the energy of the nodes is of great importance. Furthermore, in a BBN, network topology changes frequently especially when the WBAN keeps encountering other WBANs. The interference issue that results from such a dynamic scenario was investigated in our previous work [2] from a game theoretic perspective. Then, since the

¹A WBAN in our work represents a person equipped with wearable devices [7].

quality of links between WBANs keeps changing frequently due to the moving people, the ability to foresee the mobility of WBANs is crucial. All these issues are taken into account in this work. It is worth noting that a security module is also needed to ensure inter-WBAN data privacy and to provide legacy for epidemic source tracing and quarantine by the authorities, but it is not the scope of this paper and would be considered as part of our future work.

This paper is organized as follows. In section II, we discuss the existing works. In section III, we first provide the reader with some background on epidemic spread and control models and then we present our BBN-based epidemic control approach. In section IV, we introduce our BB-LAR protocol and our epidemic control mechanism, which we evaluate in section V through targeted simulations. Finally, section VI concludes the paper.

II. RELATED WORK

Actually, few works have focused on inter-WBAN communications and routing, and the most notable are discussed hereafter.

To increase the lifetime of the WBAN network, the authors in [8] used an energy-efficient secure cluster formation technique for inter-WBAN communication, based on the residual energy of the Personal Server (the sink node) and the distance between two communicating WBANs. They stated that modeling inter-WBAN communications as a hierarchical structure has the advantage of local data processing, which reduces the network overhead and provides a scalable solution.

Again, to enable inter-WBAN communications, authors of [9] implemented the network clustering algorithm proposed in [10], which detects meaningful clusters and helps in the delimitation of communities in large social networks, so that for example, two people who share many friends would be clustered in the same community. Such BBN density gives rise to a high probability of mutual interference. Then, they also proposed in [9] an inter-WBAN scheduling scheme that detects and responds to every inter-WBAN interaction and allows an optimal channel-utilization reuse.

Another concern for epidemic data aggregation and routing is the BBN topology which is subject to random changes due to WBANs' mobility. The work in [11] presents a comprehensive configurable mobility model (MoBAN) for evaluating intra and extra-WBAN communication. It implements different postures as well as individual node mobility within a particular posture.

Authors in [12] investigated the inter-WBAN routing problem in an urban critical and emergency scenario, where a BBN is considered as an extension to existing public safety networks, in order to enhance QoS and ensure ubiquitous coverage during and after a disaster. Different classes of routing protocols (OLSRv2, AODVv2, Directed Diffusion, and GPSR) were evaluated in terms of delay, reliability, and energy consumption, and it was concluded that geographic routing protocols could be a considerable candidate for BBNs.

Yet, to the best of our knowledge, our paper is the first to propose a location-based routing for BBNs, in order to ensure real-time epidemic control within a limited area. Our inter-WBAN routing protocol is based on some ideas taken from epidemic spread modeling that specifies the different stages of the pandemic evolution, which are expressed in terms of health status thresholds. The epidemic control is then ensured by the epidemic message exchange among WBANs and with the authority's wireless infrastructure, so that each WBAN informs the network of his health status in order to facilitate the quarantine strategy.

III. SYSTEM MODELS

In this section, we first give the reader some background on epidemic spread modeling, which serves as a basis for our epidemic control and BBN-based routing protocol described in Section IV. Then, we present our two-level epidemic control framework to ensure on one hand self-control actions by WBANs and on the other hand quarantine actions by authorities.

A. Background on epidemic spread modeling

The establishment and spread of infectious diseases is a complex phenomenon with many interacting factors. For example, the *epidemiology compartmental models* serve as a mathematical framework for understanding the complex dynamics of these systems, by abstracting the population into compartments under certain assumptions. These compartments represent their health status with respect to the epidemic specific features, and in the simplest case, can stratify the population into two health states: susceptible to the infection (often denoted by S); and infected by the pathogen (given the symbol I). More general models (called SEIR models) introduced two additional states; the *Exposure* state E , which is the incubation period of infected individuals before reaching the infectious state, and the *Recovered* state R , which represents the recovered people that are discarded from the epidemic zone. The mathematical framework of the SEIR model has been thoroughly investigated in the literature [5], [6], [13], through differential equations derived from the fundamental equation:

$$S + E + I + R = N,$$

Note that the population size N in the previous studies is considered constant because of the rough assumption that arrival and departure rates are equal. However, in realistic scenarios, like those considered in our work, N is in general variable.

B. BBN-based epidemic spread model

Accordingly, in this work, we rely on some ideas taken from SEIR models and we consider a dynamic system where individuals (i.e., WBANs) can enter and leave the network with different rates (hence N is not constant). The goal is to prevent in real-time the contact with the infectious individuals and provide rapid quarantine strategies based on real-time health information exchanged between cooperative WBANs

and with the medical staff, as explained later in the next section.

In such a dynamic scenario, we divide the operating time of the whole system into a set \mathcal{T} of consecutive epochs. To ensure a real-time detection of the epidemic outbreak during the incubation period of the disease, we consider, as in the SEIR models, in addition to health states S and I , the *Exposure* state E , where infected individuals should be quarantined rapidly, and the *Recovered* state R corresponding to individuals discarded from the epidemic area. Thus, we model the epidemic spread evolution in the airport indoor environment as given in Fig. 1.

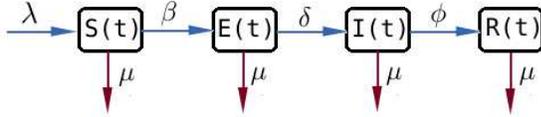


Figure 1: Our epidemic spread model flow

$S(t)$ is used to represent the number of individuals (or WBANs) not yet infected with the disease at time $t \in \mathcal{T}$, or those susceptible to the disease. $E(t)$ represents the Exposed individuals in the latent period, during which the individual is said to be infected but not infectious. $I(t)$ denotes the number of individuals who have been infected by the disease and are capable of spreading the disease to those in the susceptible category. $R(t)$ is the compartment used for those individuals who have been infected and then removed from the observed area, either due to immunization or death. Note that in our scenario, the recovered status corresponds to the quarantined individuals who are just discarded from the airport zone.

λ represents the average arrival rate, β the contact rate between susceptible and infectious individuals, δ the average transition rate from the exposed to the infectious status and ϕ that from the infectious to the recovered status. $\frac{1}{\delta}$ denotes, then, the average latent period. Accordingly, $\frac{1}{\phi}$ models the average infectious period, and μ the average departure rate.

The proposed approach aims at guaranteeing a low epidemic spread of the disease, and hence is built upon an epidemic limitation-aware routing protocol, which in turn uses an epidemic-based routing metric based on the following epidemic components:

$$\beta S(t)I(t), \quad \forall t \in \mathcal{T} \quad (1)$$

$$\delta E(t), \quad \forall t \in \mathcal{T} \quad (2)$$

$$\mu(E(t) + I(t)), \quad \forall t \in \mathcal{T} \quad (3)$$

Expression (1) aims to minimize the contact between Susceptible WBANs and Infected WBANs in order to reduce the contact rate and the epidemic spread in the indoor airport zone. Expression (2) will anticipate the translation of the incubator WBANs to the Infectious stage, by quarantine strategies during the latent period. Finally, expression (3) helps in preventing the diffusion of the disease to the external population, so that individuals who already show symptoms, either in latent

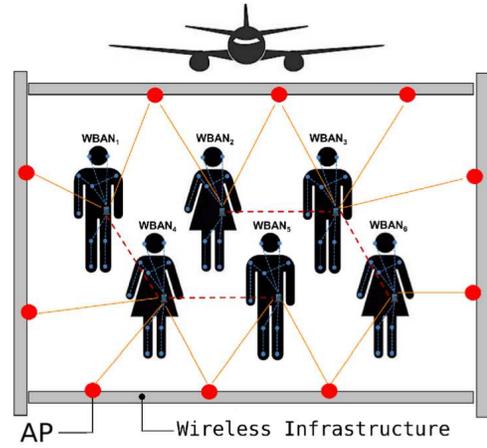


Figure 2: BBN and authority levels of the epidemic control framework in the airport indoor environment

period or in infectious stage, should be tracked and quarantined before leaving the airport control zone.

C. BBN-based epidemic control framework

To ensure an efficient epidemic control under the above considered model, we propose a two-level system framework (illustrated in Fig. 2), based on a dynamic BBN network and an existing wireless network infrastructure:

- **BBN-level control:** the real-time interactions between WBANs inside the airport play an important role in the self-prevention phase. We assume that each WBAN will be able to i) sense and broadcast his own health status, and collect health status of his neighboring WBANs, ii) participate in the diffusion of the epidemic alerts to the BBN nodes to allow them to take self-prevention measures, and iii) use the collected health status of the network to trace his own trajectory inside the airport (in our case, in the test zone) while avoiding the hazardous zones, using an indoor localization application, like the one proposed in [14], to get accurate positions of the infected individuals carrying mobile terminals (e.g., smart phones). The BBN level performs the optimization of (1), guaranteeing a minimum level of infection.
- **Authority-level control:** the existing wireless infrastructure is provided for the authority staff in order to collect measured data through the WiFi connections of mobile terminals (smart phones) carried by WBANs within the indoor airport zone, and then perform real-time analysis to detect Exposure (E) and Infectious (I) subjects. The principal role of Access Points (APs) is to provide the authorities with specific health data, coupled with localization information to help them in epidemic source tracing and quarantine strategies. The authority level is hence responsible of the optimization of (2) and (3).

SeqID _m	Src _m	L _m (t)	Dst _n	L _n (t)	s _m (t)	e _m (t)	i _m (t)	H _m (t)	E _{res} (t)	Q _{id} (t)
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Figure 3: Structure of the RREP packet

SeqID _n	Src _n	L _n (t)	Dst _m	L _m (t)	lifespan	H _n (t)
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Figure 4: Structure of the RREQ packet

IV. JOINT EPIDEMIC CONTROL AND ROUTING PROTOCOL USING BBNs

This section presents the different modules of our joint epidemic control and routing protocol. First, the *epidemic threshold* is introduced in the next subsection, upon which the *epidemic routing metric* is based. Then, the BB-LAR routing protocol is detailed in IV-B, especially the message exchange procedure within a BBN indoor environment. Next, the route selector module is described in subsection IV-C, along with the *epidemic routing metric* which determines how the epidemic data is routed among WBANs, with respect to the residual energy, the health status of the communicating WBANs, etc. Finally, subsections IV-D and IV-E discuss some epidemic control actions to be taken to stop the progression of infectious diseases.

A. Epidemic threshold

The concept of epidemic threshold, denoted hereafter as EP_{th} , is core in our framework. Both BBN-level and central authority-level epidemic control actions articulate around this configurable metric. In our model, we assume that each WBAN $n \in N$ has a social/cooperative behavior and should be able to detect his own health status and broadcast an epidemic alert to the other WBANs in case of incubating or infectious status. We define the health status $H_n(t)$ of WBAN $n \in N$, at time epoch $t \in \mathcal{T}$, as the function $f(\Gamma_n, t)$ of the correlated sensor data $\gamma_{i,n}(t) \in \Gamma_n$ of WBAN n , according to the epidemic detection predefined algorithm, where Γ_n represents the set of collected sensor data of WBAN n :

$$H_n(t) = f(\Gamma_n, t), \quad \Gamma_n(t) = \{\gamma_{i,n}(t), \forall \text{ sensor } i \in \text{WBAN } n\} \quad (4)$$

In order to keep our BBN-based epidemic spread model practically tractable, we use the discrete representation of the health status as follows:

$$H_n(t) = \begin{cases} 2, & \text{if } f(\Gamma_n, t) > EP_{th}; & \text{Infectious WBAN (I)} \\ 1, & \text{if } \epsilon < f(\Gamma_n, t) < EP_{th}; & \text{Exposed WBAN (E)} \\ 0, & \text{otherwise;} & \text{Susceptible WBAN (S)} \end{cases}$$

B. Epidemic threshold-based Location-Aided BBN Routing (BB-LAR) protocol

A neighborhood discovery module is necessary to deal with WBAN mobility and discover the dynamic routes to each other as well as to APs that forward the measured data to the medical servers. Yet, we opt for a reactive (on-demand) routing for inter-WBAN communications and epidemic control information exchange. However, due to the energy and delay high-constrained nature of BBN networks, it is required that

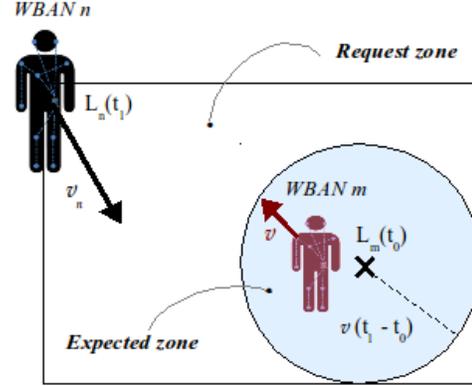


Figure 5: Expected zone and request zone for the BB-LAR routing protocol.

BBN nodes (or WBANs) do not deplete their energy in continuous routes maintenance, sharing and storing all network topology information and unnecessary routes discovery. This network overload could be avoided by implementing a geographical location based routing protocol. Therefore, in this work we focus on such a class of routing protocols, which combine reactive routing, based on dynamic source routing, and geographic routing by limiting the propagation of Route Request (RREQ) packets to a geographic region, where it is most probable for the destination to be located [15]. Such location information may be obtained by using a well-suited indoor location service among the ones discussed in [14]. This service offers ubiquitous positioning of mobile terminals in a pervasive environment, and thus allow us to reduce the search space for a desired route and may result in fewer route discovery messages.

Now, the proposed Location-Aided BBN Routing (BB-LAR) protocol, which is an epidemic threshold-based BBN routing scheme, performs as follows: When a source WBAN n needs to send data to the authority-level control or send a message to another WBAN m , he broadcasts a RREQ. The RREQ message contains several key bits information: the source, the destination, their respective location information, the lifespan of the message, a sequence number which serves as a unique ID, and the $H_n(t)$ index, specifying the health status generated by WBAN n , which determines the priority of the data he will send (see Fig. 4).

WBAN n defines a *request zone* for the route request. Assume that the current time is t_1 . WBAN n can determine the request zone based on the knowledge that WBAN m was at location $L_m(t_0)$ at time t_0 . For instance, if WBAN n knows that WBAN m travels with average speed v , then the expected zone is the circular region of radius $v(t_1 - t_0)$, centered at

location $L_m(t_0)$; an illustration is given in Fig. 5. Then, a neighbor of WBAN n forwards a route request only if it belongs to the request zone.

When a neighbor of WBAN n receives the RREQ message he has two choices:

- If he is the destination m or if he knows a route to the destination, he sends a Route Reply (RREP) message back to WBAN n , he adds his health status $H_m(t)$, his residual energy $E_{res}(m)$ and the number of susceptible, exposed and infectious WBANs; $s_m(t)$, $e_m(t)$ and $i_m(t)$, respectively, he has already exchanged with them (see Fig. 3).
- Otherwise, and if the WBAN belongs to the request zone, he will rebroadcast the RREQ to his neighbors. The message keeps getting rebroadcasted until its lifespan is up.

If WBAN n does not receive a reply within a given timeout, he rebroadcasts the RREQ with a longer lifespan and a new SeqID number. All WBANs use the Sequence number in the RREQ to ensure that they do not rebroadcast a RREQ. The BB-LAR protocol, as well as the different epidemic control modules, are summarized in the flow chart of Fig. 6.

C. BBN Route selector

To select the route to his destination, WBAN n uses the network information collected in his routing table. The purpose is to trade off between the health data transmission priorities and the network resources. By expression (5), we define the Epidemic threshold-based Routing Metric $ERM_n(t)$ that allows WBAN n to broadcast his health status or send his sensor data to the authority control, at time epoch $t \in \mathcal{T}$, while maximizing the alerts about the critical health status of BBN nodes collected from the RREP messages, according to the above expressions (1), (2), and (3).

$$ERM_n(t) = \alpha E_{res}(t) + \beta s_n(t) i_n(t) + \delta e_n(t) + \mu (e_n(t) + i_n(t)) + H_n(t) Q_{id} \quad (5)$$

α is a weighting coefficient that permits to scale the energy consumption beside the epidemic rates (β , δ and μ) and the health status ($H_n(t)$). The health status permits also to scale the consideration of the QoS metrics of the available routes, so that priority increases with data criticality ($H_n(t)=2$ for status (I), 1 for (E) and 0 for (S)).

D. Human trajectory tracing - WBAN selfish strategy

In this section, we assume that all WBANs are completely cooperative and wish to contribute to limit the progression of the disease. Based on the information collected from RREP messages, WBAN n updates his routing table with the total number of susceptible, infectious and exposed individuals in his neighborhood, the total residual energy and the QoS metric of each route. Then, he calculates the Healthy Distance $D_H(i)$ from each infectious neighbor $i \in I(t)$. Based on *mobility prediction* algorithms [16], he calculates the hazardous zones around these critical WBANs. WBAN n uses these location

parameters to trace his own trajectory, while avoiding the hazardous zones, so as to minimize his contact with infectious WBANs and ensure real-time self prevention.

E. Epidemic source tracing - Authority quarantine strategy

To effectively identify epidemic sources and inhibit epidemic spread, an accurate and real-time source tracing algorithm is needed. The APs main task is to collect specific sensor data coupled with WBANs locations and forward these information datasets to the medical servers, where online analysis and identification algorithms based search are performed to detect epidemic outbreaks and quarantine the epidemic WBAN sources.

V. PERFORMANCE EVALUATION

The Castalia-3.2 simulator [17], based on OMNet++, is used to evaluate the performance of our proposed BBN routing protocol, along with the underlying epidemic control components (corresponding to the different epidemic states) in the mass gathering area, i.e. the airport.

A number of mobile WBANs, varying in the range [20,100], is randomly deployed in a $200 \times 200m^2$ area; they move according to the common *random waypoint mobility model*. The transmit power used in our simulations is $-15dBm$ for all WBANs and the initial WBAN energy is 18720 Joules, which is the equivalent of 2 AA batteries [18]. The transmission data rate is set to 5 packets per second, and the RSSI transmission threshold to $-89.3dBm$.

In this work, we evaluate the effect of the WBAN density on three key performance metrics of routing protocols: the *Packet Delivery Ratio* (PDR), the *end-to-end delay* and the *total consumed energy*. We further compare these metrics between the three health-type traffic components, $I(t)$, $E(t)$ and $S(t)$, to prove the effectiveness of the epidemic control function of our routing protocol.

Given the scarcity of inter-WBAN routing protocols, we compare BB-LAR to the *Reliable Routing Technique* (RRT) proposed in [19], which is also a geographic routing protocol that aims establishing reliable and continuous communications between the rescue team and the people in disaster situations, without the use of the communication infrastructure, which could be completely or partially damaged. RRT introduces the notion of priority for mobile devices; the nearest mobile device to the destination is given the highest priority and is the first selected to route the data packet. If ever a forwarder device is unable to forward the data packet due to movement of mobile devices, the next priority device forwards the data packet to the destination, ensuring thus the reliability of data delivery in the ad hoc network. The difference with respect to BB-LAR is that in the RRT protocol the rescue officers are not equipped with tiny/wearable sensors, but only with communicating mobile devices (smart phones, laptops,...). The BB-LAR protocol further considers traffic classes, with respect to the different data priorities transmitted by the sensors, which is not the case of RRT. Another issue that RRT should deal with is the traffic overhead due to the multiple transmissions

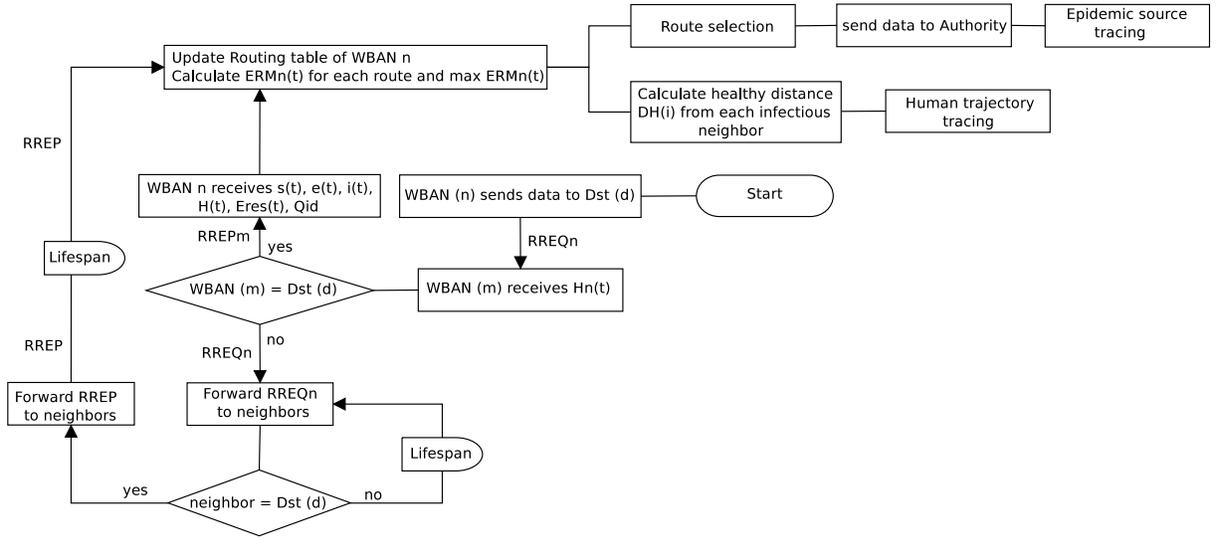


Figure 6: Flow chart of the epidemic control and BB-LAR protocol

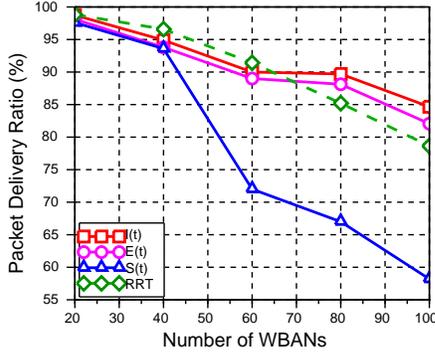


Figure 7: Packet delivery ratio of the epidemic data traffic

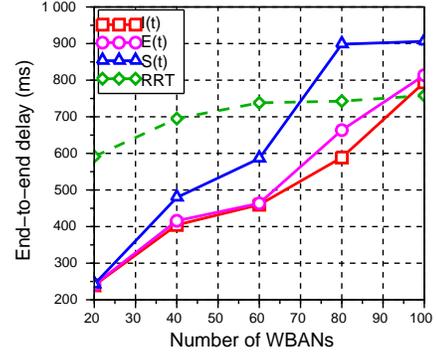


Figure 8: End-to-end delay of epidemic data packets

of data packets for reliability insurance, which can have a dramatic impact over the energy consumption and the data delivery delays. A simulation time of 2000s is considered for every WBAN density configuration, with both BB-LAR and RRT protocols, and the numerical results are reported hereafter.

The curves in Fig. 7 illustrate the effect of WBAN density on the PDR for the three health-type data traffic. The PDR metric is defined as the ratio of the average data packets received by the WBAN destinations to those generated by the WBAN sources. We define the PDR metric, for example for $I(t)$, as follows:

$$\text{PDR}(I(t)) = \frac{\sum \text{Received } I(t) \text{ data packets}}{\sum \text{Sent } I(t) \text{ data packets}}$$

As expected, the PDR metric decreases with WBAN density, for the three health-type traffic components. Nevertheless, Infectious, $I(t)$, and Exposed, $E(t)$, status packets are delivered with higher PDR, because they are prioritized: $H(t) = 2$ and $H(t) = 1$, respectively, while ordinary health status packets of $S(t)$ traffic, $H(t) = 0$, are less reliably delivered. Besides,

with higher densities (i.e., beyond 40 WBANs), we notice that the PDR dramatically decreases for $S(t)$ traffic, because the network resources become entirely occupied by Infectious and Exposed data traffic, which represent the hazardous individuals to be quarantined.

Thanks to the reliability module, the RRT protocol achieves a high PDR, which can be observed from Fig. 7. It is clear that the PDR performance of RRT is better than BB-LAR, staying above 90%, for network sizes of less than 70 WBANs. For greater network sizes, BB-LAR shows better performance than RRT for the $I(t)$ and $E(t)$ components. Indeed, for higher densities, a large number of packets corresponding to susceptible WBANs traffic $S(t)$ are delayed, and prior $I(t)$ and $E(t)$ packets are transmitted, so that to ensure that the requested PDR is met. However, RRT keeps transmitting, with much more overhead due to its reliability mechanism, the whole data traffic which results in a harmful effect on the packet delivery ratios.

The end-to-end delay specifies the average time that a data packet takes to reach the destination WBAN, including all delays caused by route discovery, buffering and queuing at each WBAN queue. End-to-end delay naturally increases with

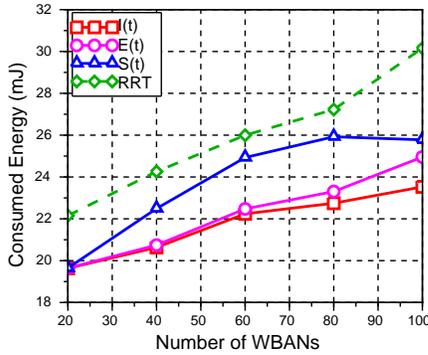


Figure 9: Total energy consumed by the epidemic data traffic

WBAN density, as shown in Fig. 8.

Since $I(t)$ and $E(t)$ packets are delay sensitive, they obtain a lower transmission delay compared to ordinary packets $S(t)$. In accordance to what was observed for the PDR metric, the $S(t)$ status latency notably increases with higher densities (above 60 WBANs), since network queues become overloaded with $I(t)$ and $E(t)$ traffic.

Due to the traffic overhead, RRT is subject to excess delay compared to BB-LAR, but its curve approaches that of $I(t)$ and $E(t)$ for network sizes above 80 WBANs. Then, for bigger networks, RRT performs almost similar to BB-LAR. Indeed, both geographic protocols limit the destination zone, and even if RRT seems to perform efficiently for large-scale networks, our enhanced BB-LAR protocol performs better for any network size, thanks to the traffic classification that differentiates the $S(t)$ traffic which is not delay sensitive, and transmit within short delays the more constrained data packets, $I(t)$ and $E(t)$.

Finally, Fig. 9 points out how the energy consumption increases with WBAN density. The consumed energy is calculated for each WBAN as the sum of transmission, buffering, reception, and idle energy amounts. Average total consumed energy values are represented. It can be observed that $I(t)$ and $E(t)$ packets are less energy consuming since they are associated with high priorities and hence face less packet retransmissions, while $S(t)$ packets need more retransmissions especially with higher densities. The gap between RRT and BB-LAR is more evident for the energy curves. Especially for big-sized networks of above 80 WBANs, packets need to pass through more nodes to reach the destination, which engenders further energy consumption, and with all packets retransmissions, as required by the RRT reliability mechanism, this energy amount would be double or even more.

To summarize, despite the overhead cost due to the epidemic information exchange packets, which is indeed quite limited, BB-LAR achieves better performance than RRT, in terms of end-to-end delay and energy consumption.

VI. CONCLUSION

In this paper we proposed a BBN-based epidemic control framework, built upon BB-LAR routing protocol, which en-

ures epidemic data exchange based on an epidemic routing metric. Our approach is inspired by the SEIR epidemic spread model that introduces the intermediate exposure status, in order to ensure real-time epidemic control, i.e., during the incubation period of the disease. The epidemic threshold is then used to detect the incubating or infectious states and warn the authority unit. The location aided routing of the epidemic alerts would inform the neighboring WBANs of the nearby peril. Finally, we evaluate BB-LAR in realistic BBN scenarios and we differentiate between three-type epidemic traffic to prove that BB-LAR achieves acceptable PDR, end-to-end delay and energy consumption values, especially for the prioritized epidemic data. Nevertheless, to effectively identify epidemic sources and inhibit epidemic spread, an accurate and real-time source tracing algorithm is needed, which will be considered as part of our future work. Furthermore, we plan to propose an analytical BBN-based epidemic control approach and compare it to relevant existing mathematical epidemic control frameworks.

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