# BIONETS: Bio-Inspired Networking for Pervasive Communication Environments

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*Abstract*— **In this paper, we present BIONETS, a novel bio-inspired approach to the design of localized services in pervasive communication/computing environments. Conventional networking approaches are not suitable for such scenarios, where they face three main issues: heterogeneity, scalability and complexity. Our solution draws inspiration from the living world, in terms of (i) evolutionary paradigms able to drive the adaptation process of autonomic services (ii) social paradigms for the provisioning of the necessary cooperation mechanisms. The net result is the introduction of autonomic self-evolving services, able to adapt to localized needs and conditions while ensuring the maintenance of a purposeful system. Such system require a scalable support from the communication standpoint. In networking terms, this results in the introduction of a two-tier architecture, based on localized opportunistic exchanges of information. The presented approach is able to achieve better scalability properties when compared to more conventional communication approaches.**

*Index Terms*— **pervasive communication, bio-inspired solutions, sensor networks, opportunistic communications, relay protocols**

## I. Introduction

One of the major trends in the communication and computing fields is related to the arising of *pervasive communication/computing environments*, characterized by an extremely large number of embedded devices [1], [2]. Such devices will possess sensing/identifying capabilities, making it possible for user-situated services to interface directly with the surrounding environment and thus entailing the possibility of introducing radically novel services, with a major impact on the way people-technology interactions are conceived today.

These pervasive communication/computing environments presents three main challenges to the conventional networking approaches: *heterogeneity, scalability and complexity*.

First, heterogeneity comes from the observation that there will be a huge differentiation in the devices forming the future ubiquitous network. Indeed, we are facing, on the one hand, the diffusion of complex portable devices with a large amount of unused processing power (e.g., laptops, PDAs, smartphones etc.). On the other one, there is a technological trend toward the embedding of miniaturized devices with sensing/identifying and basic communication capabilities in the objects surrounding us in our everyday life. The Internet paradigm, based on a "one size fits all" concept, fits badly into such heterogeneous framework. We hence propose to split the nodes of the future pervasive communication environment into two categories, based on their technical features, with different logical roles in the network. The resulting network will present a two-tier architecture, based on the distinction between cheap, tiny sensor nodes (called "T-Nodes") and powerful, complex, mobile devices (termed user nodes or, simply, "U-Nodes") [3]. The first ones have very limited communication capabilities, and could not possess a complete protocol stack. They are used to sense/measure a physical phenomenon, and transmit such information to the interested U-Nodes. No communication among T-Nodes is encompassed, so that, with respect to the conventional sensor networks approach [4], we are freeing the sensors from the burden caused by store-and-forward operations, allowing for smaller, cheaper and longer-lasting devices. U-Nodes can "poll" the nearby T-Nodes and communicate among them when they get into mutual communication range.

Second, the end-to-end paradigm typical of Internet-based communications, although having successfully survived the last 30 years, suffers from insurmountable scalability problems when applied to large-scale wireless environments. This is the lesson that can be learned from the seminal work of Gupta and Kumar on the capacity of wireless networks [5]. Subsequent works have further investigated the topic, achieving the conclusion that the imposition of a strict connectivity requirement may negatively impact the network capacity [6], [7]. Furthermore, it has been later shown by Grossglauser and Tse that it is possible to obtain a scalable network by dropping the connectivity requirement and exploiting nodes mobility to convey information [8]. In this paper, we present two mechanisms aimed at improving network scalability. The first one works at the U-Nodes level, and exploits the mobility of devices to convey information. No network connectivity is required *a priori*, and the resulting topology is an archipelago of connected islands of nodes. Information is exchanged locally in a peer-to-peer fashion through single-hop broadcasting, and is diffused by (i) local relaying of packets (as in conventional MANETs [9]) (ii) opportunistic exchanges when mobile devices come into mutual communication range [10]. All communications are local in nature, and such localized exchanges of information substitute the end-to-end conventional communication approach. As a consequence, there is no need for both addressing and routing. All the operations on information exchanges will be driven locally by the services. The second mechanism exploits the locality (in both space and time) of information coming from the environment. The basic concept is that data originating from sensors loose their usefulness (i.e., information content) as soon as they spread (in both time and space domain). In other words, by transmitting sensors-gathered information in an end-to-end fashion we

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would overload the network with data carrying a potentially low information content. We propose a mechanism, called Information Filtering, which reduces the overhead of data packets with low information content by filtering the packet flows based on their age and traveled distance.

The third issue is complexity, related to the need of controlling and maintaining the network functionalities. The first problem here comes from the disconnected nature of network operations. In this case, indeed, conventional centralized solutions cannot be applied, and we need to resort to a distributed management paradigm. On the other hand, we are in the presence of a system potentially comprising billions of interacting nodes. This impacts both the complexity and the scalability of the control mechanisms themselves (in large-scale systems the amount of regulation needed usually increases as a superlinear function of the number of nodes). Handling the complexity of the resulting network is therefore a challenging task, that requires a non-conventional distributed approach (also in view of the necessity of supporting disconnected operations) to network management, able to organize the complexity of such environments into a purposeful system. To do so, we need to define a framework for providing stable operations and service management functionalities (i.e., configuration, performance, accounting, fault and security) in a fully distributed and decentralized way. Given the unfeasibility of the conventional centralized approaches, a possible solution is to resort to self-managing "autonomic" systems [11]. These systems are inherently self-configuring, self-optimizing, self-healing and self-protecting; further, such features are achieved in a distributed scalable way. While autonomicity has been proposed as the possible paradigm for next-generation communication systems [12], there is no common agreement in the scientific community on how to build systems able to present such desirable properties. In our networking framework, services are user-situated. We can exploit this fact, together with the observation that all network operations (e.g., information filtering and data exchanges) are in charge of the running services, to re-conduce the problem to the identification of a suitable approach for enabling autonomic services. Abstracting, we need to introduce a distributed mechanism able to predict and control the behavior of a large-scale, complex, heterogeneous system. Our approach draws inspiration from the living world, since nature has been confronted with (and successfully resolved) the problems of scale, complexity and diversity for a rather long time. In particular, we envisage *adaptation by evolution*, the way organisms evolved in nature, as a possible paradigm for the introduction of autonomic services. Without going into the details, which are out of the scope of the paper, we can build a one-to-one mapping between biological entities and their technological counterparts, and introduce a distributed framework for service evolution able to mimic what happens in the living world [13]. In such framework, a key role is played by cooperation and trust/reputation mechanisms, which will be built around paradigms from the social world. The result is what we call BIONETS, i.e., a network that looks like a living ecosystem, where services play the role of organisms, evolving and combining themselves to successfully adapt to the environmental characteristics (comprising network topology, service dynamics etc.).

Looking at this from the communication point of view, the result is a simple system, based on a two-tier architecture (i.e., the U-Nodes plane and the T-Nodes one) where information spreads according to the user mobility pattern and is filtered to preserve the system from overflowing. In this paper, we detail such network architecture, called SOCS (Service-Oriented Communication System), and evaluate its performance by means of a suitable stochastic model of the system operations.

The remainder of this paper is organized as follows. In Sec. II we introduce and detail the SOCS architecture and the information filtering mechanism. A simple stochastic model for assessing network performance is presented and validated against simulation outcomes in Sec. III. Sec. IV concludes the paper pointing out open issues for future research.

## II. Service Oriented Communication Systems

The devices forming future pervasive environments may communicate to each other, forming a large-scale network, whose specific features are far from those of existing models. First, this network will comprise a huge number of nodes and experience a potentially tremendous amount of data flows, raising scalability issues for the underlying networking infrastructure. Further, these scenarios will be characterized by very heterogeneous devices, ranging from small embedded sensors, TAGs and RFIDs to complex and powerful mobile phones and laptops. Information will be gathered from the surrounding ambient through sensing/identifying devices, enabling context-awareness and interactions with the environment.

Moreover, one key requirement in conventional networking approaches is connectivity. In networks of wireless devices, channel randomness and nodes mobility hurt the possibility of getting an always fully connected topology [14], [15]. While network connectivity could be ensured by enhancing the transmission power of the nodes, such a choice is known to be harmful for the scalability of network capacity [6]. A network with better scalability properties may be achieved moving from a connected topology to an archipelago of disconnected islands; nonetheless this requires the introduction of novel approaches for supporting disconnected operations.

These factors call for a novel approach, able to overcome the limitations of conventional solutions to pervasive environments by gradually shifting the end-to-end communication paradigm toward an autonomous service-oriented model, realizing what we call a Service-Oriented Communication System, SOCS hereafter.

The SOCS communication model assumes services to be at the hearth of the system, and assumes the exchanges of information to be driven by service *requirements*. Applications, running on users portable devices, will be augmented by localized information originated from sensors, and by opportunistic exchanges of information with other mobile users encountered on-the-move. Without the notion of end-to-end communication, the service is in charge of autonomously defining the actions to be taken, deciding which data, gathered from sensors, should be relayed to other users, the users to exchange information with etc.

### A. A Two-Tier Network Architecture for Pervasive Communication Environments

The SOCS communication model is based on a two-tier network architecture, as detailed in [3], where nodes are divided into two broad categories depending on both (i) their functional role in the network (ii) the computing/processing/communication capabilities they possess. The first class of devices, the "T-Nodes" represents cheap, tiny devices such as sensors, tags and RFIDs. They possess sensing/identifying capabilities, with small or no computing power and a minimal communication stack. In opposition to the conventional wireless sensor networks approach [4], they are not required to perform store-and-forward operations, which helps in keeping the complexity of the devices low and in increasing their lifetime. T-Nodes do not communicate among them, but just answer to poll messages sent by U-Nodes which are interested in getting the actual value of the random field they are sensing.

On the other hand, U-Nodes are devices running services. They present computing/communication capabilities, are almost exempt from energy consumption issues and may be mobile in nature. U-Nodes may communicate among them, but can also communicate with T-Nodes, reading their actual value. They act both as "sinks" for sensor-gathered data, as well as sources/relays/sinks for communication among U-Nodes. With this division we are in some sense taking to the extreme the approach first introduced in [16], where nodes heterogeneity is exploited, by means of a device-aware routing algorithm, for enhancing the network lifetime.

The communication among U-Nodes is based on opportunistic localized peer-to-peer interactions, as opposed to the end-to-end semantics of standard Internet protocols. U-Nodes communicate among them (by means of single-hop broadcast messages) just when they are in mutual communication range, and when the service running on the user device requires the interactions. Mobility of the devices is exploited to convey packets, building an archipelago of connected islands. This localized nature of the interaction matches the localized nature of the information, which is augmenting the services running on the users devices. One of the main advantages of such localized communication paradigm is that there is no need for (i) a global addressing mechanism (ii) a routing mechanism, thus lowering the complexity of the network management mechanisms. The focus is indeed not on transmitting information to a peculiar node (address-based architecture) but, rather, to all the devices running the same service in proximity (localized service-oriented communication model). The described network architecture is depicted in Fig. 1

Clearly, the applicability of the SOCS model is confined to a class of services requiring massive amount of data retrieved locally and with relaxed delay constraints [1].

Similar in spirit to our SOCS network architecture are the works flourishing in the area of delay-tolerant or opportunistic networks [17], [10]. With respect to their approach, we are not interested in maintaining the end-to-end nature of communications, but, rather, in focusing on localized interactions only. Common points with such approaches are the need for disconnected operations, which are handled, at the data transport level, by means of a relay protocol.

[1]We can nonetheless think of a backbone network that, when present, may provide shortcuts to address remotely located data/services.

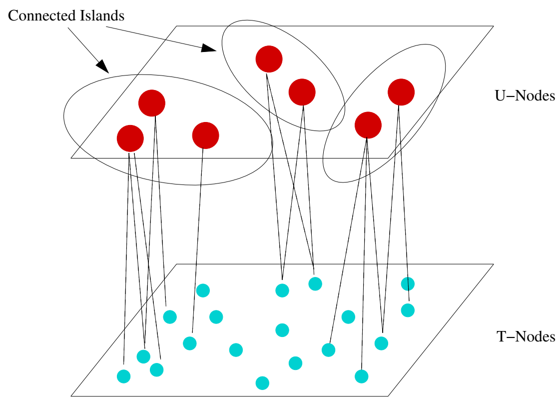



Fig. 1. The two-tier SOCS network architecture.

Without assuming any backbone for conveying high volumes of data, information flow is generated solely by the physical movement of users, together with the opportunistic exchange of data. Contextual information, which is generated from sensors and represent a key component for the functioning of pervasive services, is also diffused by means of the users' physical mobility. Clearly, this means that, for efficiently running pervasive services, an adequate level of users mobility is needed in order to provide a minimum flow of information in the environment. The coupling of users mobility with the opportunistic exchange of data is therefore considered as one of the key elements to be evaluated in the SOCS network architecture.

Moreover, as the number of sensors embedded in the environment grows, there is the risk of an explosion of the gathered and exchanged data. A mechanism is needed that, by exploiting the intrinsic locality of the contextual data generated by T-Nodes, limits the diffusion and defines an *information life cycle*. We term this mechanism *Information Filtering*, and will be deeply analyzed in the next Section.

### B. Information Filtering: Principles and Mechanisms

The SOCS approach targets the scalability issues at the U-Nodes level. In pervasive computing/communication environments, however, the number of tiny devices with sensing capabilities is expected to be some order of magnitude higher than that of user nodes. Thus, suitable techniques for limiting the diffusion of the data generated by T-Nodes is a primary need to avoid network congestion and collapse.

Information Filtering plays a central role in ensuring the scalability properties of our architecture and applies to scenarios where sensors are used to gather information from the surrounding environment, as usually the case in pervasive communication environments. Consider a U-Node that issues a query at time $t$ from position $(x, y, z)$, concerning the value of a given random field $X$. A nearby sensor will answer with the data measured at its location $(x_0, y_0, z_0)$ at time $t_0$.

Clearly, the larger the distance between the sensor and the user, and the longer the time it takes for the packet to arrive to the U-Node, the lower the usefulness (i.e., the information content) conveyed by the data. Roughly speaking, the packet would contain information that is of little relevance due to its low correlation with the actual query. From a sensor-centric perspective, we may then say that, for such kind of data, the information content decays over both time and space. On the other hand, from the user point of view, we define a "sphere of interest" that surrounds (again in time and space) the user's device and defines the local environment.

To formalize such concept, we consider a stationary ergodic random field $X$, defined on a suitable probability space $\{\Omega, \mathcal{F}, \mathbb{P}\}$ and taking values in a finite set $\mathcal{S}$. We denote by $\pi(\cdot)$ the stationary measure of $X$ over $\mathcal{S}$. Devices with sensing capabilities are spread in the environment and may get a precise estimation of the field $X$ when asked to. Such data is encapsulated in a packet and broadcasted [2]. Now, let us assume that a sensor located at $(x_0, y_0, z_0)$ takes a sample of the field $X$ at time $t_0$. The value $X(x_0, y_0, z_0, t_0)$ is then coded, packetized and transmitted. From basic information theory concepts [18], the minimum amount of bits necessary to code the data equals its entropy:

$$H(X) = -\sum_{x \in \mathcal{S}} \pi(x) \log \pi(x). \tag{1}$$

This applies to the classical communication case, in which we are interested in a perfect reconstruction of the information content at the receiver side. However, consider that the packet containing $X(x_0, y_0, z_0, t_0)$ is received at $(x, y, z, t)$, so that the real information needed is $X(x, y, z, t)$. Then, the actual information content of the data packet (and the number of bits needed to encode it) may be measured in terms of the mutual information [18]:

$$I(x, y, z, t; x_0, y_0, z_0, t_0) = H(X) - \xi, \tag{2}$$

where $\xi = H\left(X(x, y, z, t) | X(x_0, y_0, z_0, t_0)\right)$. As time and space shift increases, the data content becomes less and less correlated with the information needed, so that $\xi \rightarrow H(X)$ and the mutual information tends to 0. This, in turn, implies that the data packet could be (ideally) shrinked as it travels over time and space without loosing, from the communication point of view, any information content. The optimal coding scheme would adjust the data packet length matching its information content. This optimal approach, while not practically feasible, would play a key role in solving the data scalability problems in massively dense networks [5], [19]. We propose a simplistic approximation of such optimal coding strategy, which consists of dropping the packet when its information content (in terms of mutual information) falls below a threshold, set to $(1-\varepsilon)$ percent of the original information content $H(X)$. This may be translated into a bound on the error probability $P_e$ by means of Fano's inequality [18]:

$$H(P_e) + P_e \log\left(|\mathcal{S}| - 1\right) \geq \varepsilon H(X). \tag{3}$$

[2]Please note that we do not consider schemes able to exploit the availability of side information, but assume each sensor codes its data independently.

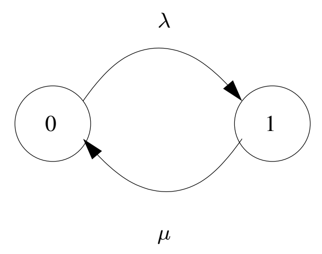



Fig. 2. Model of the process $X(\cdot)$, sampled by the sensor node, as a two-states Markov chain.

To show the functioning and effect of such information filtering mechanism, we consider a simple two-states Markovian model for a sensor placed at $(x, y, z)$, as depicted in Fig. 2. This binary model is chosen for its simplicity, but is still able to cover a rather wide range of applications, in which sensors control whether a physical quantity exceeds a given threshold. Examples may include surveillance and environmental monitoring, resources availability and domotic applications. The process $Y(t) = X(x, y, z, t)$ takes values in $\mathcal{S} = \{0, 1\}$ and is characterized by the transition rates $\lambda$ and $\mu$. The limiting probabilities are $(\pi_0, \pi_1) = (\frac{\mu}{\lambda+\mu}, \frac{\lambda}{\lambda+\mu})$, and we assume that the time instants at which the source is read follow a Poisson law, so that Slivnyak's theorem [20] may be applied. A simple computation leads to the following expression for the process correlation:

$$\begin{aligned} R_Y(t) &= \mathbb{E}[Y(t)Y(0)] = \mathbb{P}[Y(t)=1, Y(0)=1] = \\ &= \mathbb{P}[Y(t)=1 | Y(0)=1] \cdot \pi_1 = \left(\frac{\lambda}{\lambda+\mu} + \frac{\mu e^{-(\lambda+\mu)t}}{\lambda+\mu}\right) \cdot \frac{\lambda}{\lambda+\mu}. \end{aligned} \tag{4}$$

Exploiting the binary nature of the process, we can then compute the normalized covariance of $Y$ as:

$$\rho_1(t) = \frac{R_Y(t) - \pi_1^2}{\pi_1 - \pi_1^2} = e^{-(\lambda+\mu)t}. \tag{5}$$

We assume the process $X$ to have a separable correlation structure (in the time and space domain) [21], and assume its normalized covariance to decay exponentially in space [19] with intensity $\gamma$:

$$\rho_2(d) = e^{-\gamma|d|}, \tag{6}$$

we have the following expression for the normalized covariance function of $X$:

$$\rho_X(d, t) = \rho_1(t) \cdot \rho_2(d) = \frac{\lambda\mu}{\lambda+\mu} e^{-(\lambda+\mu)t - \gamma|d|}. \tag{7}$$

From the normalized covariance, we can retrieve the expression of the mutual information, using a result from [22]:

$$\begin{aligned} &I(x + x_0, y_0, z_0, t + t_0; x_0, y_0, z_0, t_0) = \\ &= \pi_0 \pi_1 \rho_X(d,t) \log \frac{\left[1 + \frac{\rho_X(d,t)\pi_0}{\pi_1}\right] \cdot \left[1 + \frac{\rho_X(d,t)\pi_1}{\pi_0}\right]}{\left(1 - \rho_X(d,t)\right)^2} + \\ &+ \pi_1^2 \log\left(1 + \frac{\rho_X(d,t)\pi_0}{\pi_1}\right) + \pi_0^2 \log\left(1 + \frac{\rho_X(d,t)\pi_1}{\pi_0}\right) + \\ &+ 2\pi_0\pi_1 \log\left(1 - \rho_X(d,t)\right). \end{aligned} \tag{8}$$

As an example, we reported in Fig. 3 the expression of the mutual information function in the case $\lambda = 0.0033$, $\mu = 0.0017$, $\gamma = 0.0050$, $\varepsilon = 0.2$, which would represent the actual rate necessary, at time lag $t$ and space lag $d$, to convey the whole information content. Together, we also plotted the actual approach used, which transmit information at the "full rate" $H(X)$ up to a distance and time dependent on the value of $\varepsilon$. The figure is meant to provide a graphical clarification of the effect of the proposed scheme in limiting the propagation of low-information data packets in the network.

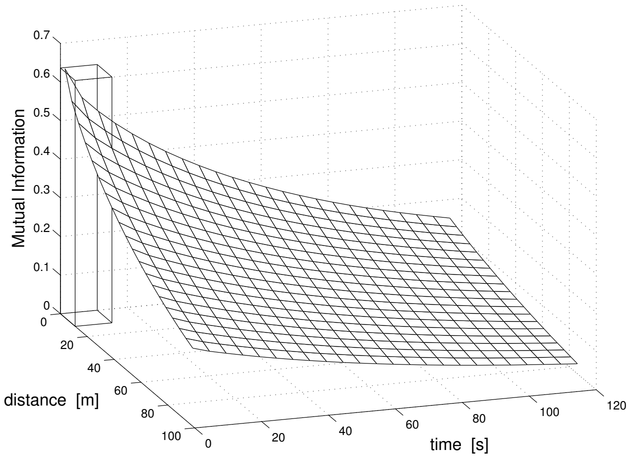



Fig. 3. Mutual information function versus time and space lags, $\lambda = 0.0033$, $\mu = 0.0017$, $\gamma = 0.0050$ and $\varepsilon = 0.2$.

## III. Key Performance Considerations in SOCS

The Service-Oriented Communication Systems architecture outlined in the previous section aims at providing a flexible and scalable support to the deployment of pervasive services. In order to do so, two mechanisms are used. The first one diffuses information by means of localized U-Nodes interactions and device mobility. The second one filters the data packets to ensure their information content exceeds a given threshold.

The critical issue of these mechanisms is their ability to provide a timely dissemination of the relevant information while at the same time preserving network scalability. In this section, we will thus present stochastic models for both information diffusion through node mobility as well as information filtering in the absence of localization data. Particular attention will be devoted to the case of users moving according to the Random Waypoint Mobility.

### A. A Stochastic Model for Information Diffusion

We consider a network of $N$ identical U-nodes, which communicate through the exchange of *messages*. Two mobile nodes can communicate if their mutual distance is below a given threshold $R$, termed the transmission range. The time the two nodes stay within mutual communication range is assumed to be long enough to transmit the whole amount of data stored in each node. Further, we introduce a factor $0 < p < 1$ which defines the probability that a communication between two nearby nodes is successful, and use it to account for noise, interference, obstacles and other environmental factors. The sequence of meeting times is modeled as a stationary renewal marked point process $\{(T_n, \sigma_n)\}_{n\in\mathbb{Z}}$ over $\{\Omega, \mathcal{F}, \mathbb{P}\}$. The points $T_n$ represent the time instants at which two nodes get in contact, while the mark indicates which nodes get into mutual communication range and takes the form $\sigma_n = (i, j)$, $i, j \in 1, \ldots, N$. In the following, we will assume the marks to be independent and identically distributed.

We assume a simple stochastic model for the spreading of the information [23]. Given a population of size $N$, we assume that at time 0 one "infected" node shows up (this corresponds to the reading of a sensor) and, consequently, $(N-1)$ "susceptibles" (i.e., which have not got the message) nodes are present. Once infected, a node remains in the infected state, and we assume that, in any time interval $h$, any infected individual will infect a susceptible one with probability $\int_0^h f(h)\mathrm{d}h + o(h)$, $f(\cdot)$ being the probability density function of two distinct users inter-meeting time (this corresponds to the probability that the two nodes get in touch). We denote by $Z(t)$ the number of infected individuals at any time $t$, correspondent to the number of copies of the message (including the original one) present at time $t$ in the network. From the assumptions made on the model, $\{Z(t), t \geq 0\}$ is a semi-Markov process over the state space $\{1, \ldots, N\}$. Further, due to the persistence of infections, the underlying Markov chain has an absorbing state at $N$ (fully infected population, i.e., message broadcasted successfully).

In order to assess the performance of the relay protocol, we need to solve the transient of the semi-Markov process. We denote by $\psi_{i,i+1}$ the time it takes to pass from state $i$ to state $i+1$, and denote by $\Psi^*_{i,i+1}(s)$ the Laplace-Stieltjes Transform (LST) of its probability density function. Since the $\psi_{i,i+1}$ are independent, the LST of the time needed for reaching state $k = 2, 3, \ldots N$, $\theta_k$, is:

$$\Theta^*_k(s) = \prod_{i=1}^{k-1} \Psi^*(s)_{i,i+1}. \tag{9}$$

The probability density function of $\theta_n$ can then be retrieved by inverting numerically (9) [24]. We can also retrieve the probability that at time $t$ there are $k$ copies of the message in the system, $p_k(t) = \mathbb{P}[Z(t) = k]$, $k = 1, \ldots, N$. This can be done by noting that:

$$\begin{array}{lcl} p_N(t) & = & \mathbb{P}[\theta_N \leq t], \\ p_{N-1}(t) & = & \mathbb{P}[\theta_{N-1} \leq t] - \mathbb{P}[\theta_N \leq t], \\ \vdots & & \\ p_2(t) & = & \mathbb{P}[\theta_2 \leq t] - \mathbb{P}[\theta_3 \leq t], \\ p_1(t) & = & 1 - \mathbb{P}[\theta_2 \leq t]. \end{array} \tag{10}$$

Denoting by $\mathcal{L}[\cdot]$ the LST operator, since $\mathcal{L}\left[\mathbb{P}[\theta_k \leq t]\right] = \frac{\Theta^*_k(s)}{s}$, and considering $\Theta^*_1(s) = s$, we have for $1 \leq k \leq N-1$:

$$P^*_k(s) = \frac{\Theta^*_k(s) - \Theta^*_{k+1}(s)}{s}, \tag{11}$$

where $P^*_k(s) = \mathcal{L}[p_k(t)]$. Numerical inversion may then by applied to obtain $p_k(t)$.

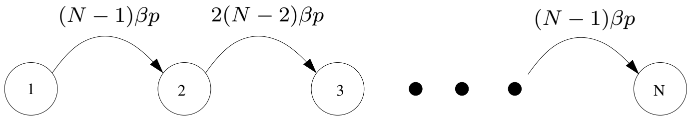



Fig. 4. Markov chain model for the number of copies of the message in the network, $Z(t)$, in the case of nodes moving according to a random waypoint mobility model.

### B. A Special Case: Random Waypoint Mobility

We now apply the previous general framework to the case of users moving according to a Random Waypoint Mobility model [25]. This particular model is generally adopted because, despite its simplicity, it is realistic enough to represent a vast class of mobility patterns.

We assume that the user nodes move at a constant speed $v$ in a square of size $L \times L$, with $L \gg R$, $R$ being the communication range. Under such assumptions, the (filtered) process $\{T_n, \sigma_n = (i,j)\}$, indicating the meeting times of nodes $i$ and $j$, can be well modeled as a Poisson point process of intensity $\beta$ [26]. Further, according to [27], the intensity of such process is approximately given by:

$$\beta \approx 2R\frac{4V}{\pi}\frac{1.3683}{L^2}. \tag{12}$$

Considering packet errors, since a randomly sampled Poisson process is again a Poisson process [28], the sequence of successful communication times between nodes $i$ and $j$ forms a Poisson process of intensity $\beta p$. The process $Z(t)$ results in a continuous-time Markov chain whose structure and transition rates are depicted in Fig. 4. Accord to (9), the Laplace-Stieltjes Transform (LST) of the time needed to reach $k$ nodes becomes:

$$\Theta_k^*(s) = \prod_{i=1}^{k-1} \frac{(N-i)i\beta p}{(N-i)i\beta p + s}. \tag{13}$$

From (13) we have:

$$\Theta_{k+1}^*(s) = \Theta_k^*(s) \cdot \frac{(N-k)k\beta p}{(N-k)k\beta p + s},$$

so that, substituting in (11), we obtain:

$$P_k^*(s) = \frac{\Theta_k^*(s)}{(N-k)k\beta p + s}. \tag{14}$$

From (13) we then have:

$$P_k^*(s) = \frac{1}{(N-k)k\beta p + s} \cdot \prod_{i=1}^{k-1} \frac{(N-i)i\beta p}{(N-i)i\beta p + s}. \tag{15}$$

The case $k = N$ needs to be treated separately, leading to:

$$P_N^*(s) = \frac{\Theta_N^*(s)}{s} = \frac{1}{s} \cdot \prod_{i=1}^{N-1} \frac{(N-i)i\beta p}{[(N-i)i\beta p + s]}. \tag{16}$$

We only present the complete inversion analysis for the case when $N$ is even, because the case $N$ is odd is similar. First, assume $1 \le k \le \frac{N}{2}$. In this case, all poles of the LST are simple ones, so that we get:

$$P_k^*(s) = \sum_{i=1}^{k} \frac{r_{k,i}}{(N-i)i\beta p + s}, \tag{17}$$

where:

$$r_{k,i} = \frac{\prod_{j=1}^{k-1} j(N-j)}{\prod_{j=1, j\neq i}^{k} j(N-j) - i(N-i)}. \tag{18}$$

Hence, we obtain:

$$p_k(t) = \sum_{i=1}^{k} r_{k,i} e^{-[(N-i)i\beta p]t} \mathbb{U}(t), \tag{19}$$

where $\mathbb{U}(t)$ is the usual step function. For $\frac{N}{2}+1 \le k \le N-1$, we get:

$$P_k^*(s) = \frac{r_{k,\frac{N}{2}}}{s + (\frac{N}{2})^2\beta p} + \sum_{i=1}^{N-1-k} \frac{r_{k,i}}{s + (N-i)i\beta p} + \\ + \sum_{i=\frac{N}{2}+1}^{k} \left[\frac{r'_{k,i}}{(s + (N-i)i\beta p)} + \frac{r''_{k,i}}{(s + (N-i)i\beta p)^2}\right], \tag{20}$$

where

$$r''_{k,i} = \beta p \frac{\prod_{j=1}^{k-1} j(N-j)}{\prod_{j=1, j\neq i, j\neq N-i}^{k} (N-j)j - (N-i)i}, \tag{21}$$

and

$$r'_{k,i} = -\frac{r''_{k,i}}{\beta p} \cdot \sum_{\substack{j=1 \\ j\neq i, j\neq N-i}}^{k} \frac{1}{(N-j)j - (N-i)i}. \tag{22}$$

Finally from (20)

$$p_k(t) = \left\{ r_{k,\frac{N}{2}} e^{-\left[(\frac{N}{2})^2\beta p\right]t} + \sum_{i=1}^{N-1-k} r_{k,i} e^{-[(N-i)i\beta p]t} + \right. \\ \left. + \sum_{i=\frac{N}{2}+1}^{k} \left[ r'_{k,i} e^{-[(N-i)i\beta p]t} + r''_{k,i} t e^{-[(N-i)i\beta p]t} \right] \right\} \mathbb{U}(t). \tag{23}$$

In the case when $k = N$, the same residual expansion takes the form

$$P_N^*(s) = \frac{1}{s} + \frac{r_{k,\frac{N}{2}}}{s + (\frac{N}{2})^2\beta p} + \\ + \sum_{i=\frac{N}{2}+1}^{N-1} \left[\frac{r'_{k,i}}{(s + (N-i)i\beta p)} + \frac{r''_{k,i}}{(s + (N-i)i\beta p)^2}\right], \tag{24}$$

where:

$$r_{N,\frac{N}{2}} = -\prod_{\substack{j=1 \\ j\neq \frac{N}{2}}}^{N-1} \frac{(N-j)j}{(N-j)j - (\frac{N}{2})^2}, \tag{25}$$

and

$$r''_{N,i} = -\beta p \frac{\prod_{j=1, j\neq i}^{N-1} j(N-j)}{\prod_{j=1, j\neq i, j\neq N-i}^{N-1} (N-j)j - (N-i)i}, \tag{26}$$

and

$$r'_{N,i} = \frac{r''_{N,i}}{\beta p} \cdot \sum_{\substack{j=0 \\ j\neq i, j\neq N-i}}^{N-1} \frac{1}{(N-j)j-(N-i)i}. \quad (27)$$

Finally, we obtain:

$$p_N(t) = \Bigg\{ 1 + r_{N,\frac{N}{2}} e^{-[(\frac{N}{2})^2\beta p]t} + \sum_{k=1}^{\frac{N}{2}-1} r'_{N,k} e^{-[(N-k)k\beta p]t} + \\ + \sum_{k=1}^{\frac{N}{2}-1} r''_{N,k} t e^{-[(N-k)k\beta p]t} \Bigg\} \mathbb{U}(t), \quad (28)$$

which can be also verified using the normalization condition.

### *C. Information Filtering in the Absence of Localization Information*

In the development of the information filtering concept, we implicitly assumed that exact position information was available at each node. This cannot be considered realistic for a network of mobile heterogeneous devices, where it cannot be assumed *a priori* that all nodes are equipped with a GPS or similar mechanism. Thus, it may be necessary to implement the information filtering mechanism based only on time-domain information[3]. All what we have is then the age of the packet. Nonetheless, we can translate the spatial limitation into a corresponding one in the time domain. This can be done by considering an approximation for the distance covered by the packet at time $t$. Such distance can be split in two components. The first one depends on the speed and direction of the U-Node. If the speed is constant, this first term is upper-bounded by $(V \cdot t)$, the bound being tight for small $t$ for a large class of mobility models. The second component comes from the "multihopping" of packets. This can be approximated by the product of the expected value of $Z(t)$ and the average per-hop advance. The latter term can be calculated assuming that the angle between the speed vectors of the two nodes meeting is uniformly distributed in $[0, 2\pi)$. The situation is shown in Fig. 5. The average progress in the radial direction is then:

$$\Delta = 2 \int_0^{\frac{\pi}{2}} f_\theta(a) \sin(a) \mathrm{d}a = \frac{R}{\pi}. \quad (29)$$

As far as the average number of hops performed up to time $t$ is concerned, we could well use the results of the previous section to find its exact value. However, to avoid introducing cumbersome algebra, we decided to use a fluid-flow approximation of $Z(t)$, denoted by $\tilde{Z}(t)$. From Fig. 4, this obeys the following differential equation:

$$\frac{\partial \tilde{Z}(t)}{\partial t} = \tilde{Z}(t)\beta p N - \tilde{Z}^2(t)\beta p, \quad (30)$$

[3]This does not require, in principle, all nodes to be synchronized to a common clock. Indeed, we assume that when a data packet is relayed from a node to a new one, the age of the data is stamped in a dedicated field in the packet header. Upon reception, the node substitutes the field with the difference between its local clock time and the packet age. The packet age can be calculated at any time instant by subtracting the timestamped value from the local clock.

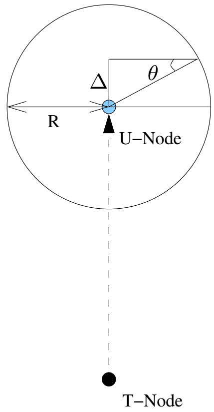



Fig. 5. Geometrical representation of the meeting process. $\theta$ defines the angle between the velocity vectors of the two devices and $\Delta$ the progress in the radial direction.

| | |
|---|---|
| Simulation area | $2000 \times 2000$ m$^2$ |
| Sensors communication range | 10 m |
| U-Nodes communication range | 50 m |
| U-Nodes speed | 4 m/s |
| U-Nodes number | $10, 50, 100, 200$ |
| U-Nodes PHY/MAC Protocol | $802.11b$ |
| Probability of successful packet transmission $p$ | 0.9759 |

TABLE I
SIMULATION PARAMETERS

with initial condition $\tilde{Z}(0) = 1$. Some easy calculation leads to the following solution of (30):

$$\tilde{Z}(t) = \frac{N e^{N\beta pt + NC}}{N + e^{N\beta pt + NC}}, \quad (31)$$

where $C$ is a normalizing constant. If $N$ is quite large, we can safely take $C = 0$ to approximate the initial condition. We then find the following approximation for the covered distance:

$$D(t) = V \cdot t + \frac{R}{\pi} \cdot \frac{N e^{N\beta pt}}{N + e^{N\beta pt}}. \quad (32)$$

By means of (32) we can approximate the distance covered by a message, and translate a limitation in the spatial distribution of a message into a corresponding limit in the "age" of a message.

### *D. Numerical Results*

In order to evaluate the performance of the proposed approach, and to validate the outcomes of the analytical framework provided, we have run extensive simulations using a freely available software package [29]. We set the square size $L$ to 2 km, the communication range $R$ to 50 m, the speed of the U-Nodes $V$ to 4 m/s and varied the number of U-Nodes. The probability of successful packet transmission has been set to $p = 0.9759$, according to the results in [30] (since one-hop broadcast transmissions are used, the successful packet transmission rate equals the complementary of the packet error rate). In Table I, we reported a brief summary of the simulation parameters used.

Each simulation was run a number of times sufficient for guaranteeing a 95% confidence interval tight enough. Each simulation was run by varying the seed number of the random number generator (RNG) in order to guarantee maximal independence among different runs.

We reproduced a *Perfect Simulation* [31], sampling the initial speed and location of nodes, moving according to a Random Waypoint Mobility (RWM) Model, from the corresponding stationary distribution, following the approach in [32]. Subsequent destinations and speeds are then sampled from the uniform distribution. This approach eliminates the time needed for the simulation to reach the stationary regime.

Users exchange data according to the relay model described in section III, and implement an IEEE 802.11b-compliant PHY and MAC layer protocols [33], [34].

We first started by analyzing the accuracy of the relaying model, and compared it to simulation results.
In Fig. 6, the state probability $p_k(t)$, as defined in (23), is plotted for $k = 10, 50$ in the case $N = 100$, and compared with simulation outcomes. At time $t^*$ a mobile user is randomly chosen to be the first *infected*, e.g. it is reading a sensor and thus generating the first message. The message is then diffused according to the networking paradigm described in Sec. II. Starting from the time instant $t^*$, the state probability $p_k(t)$ is traced as a function of time. Since a Perfect Simulation is reproduced [31], simulation starts from its stationary regime, and, thus, we can safely assume the originating message to be generated at time $t^* = 0$ from a randomly chosen U-Node. The plot is based on 10000 independent simulation runs. The graph shows that the analytical model significantly match the simulation results for low values of $k$ and $t$ [4], while it seems to anticipate the simulation outcomes for higher values, i.e. $k = 50$. Nevertheless, according to the Information Filtering principles described in Sec. II-B, limited values of $t$ is the region where Information Filtering will be applied, and, thus, lower accuracy of the analytical model for high values of time $t$ can be easily tolerated.

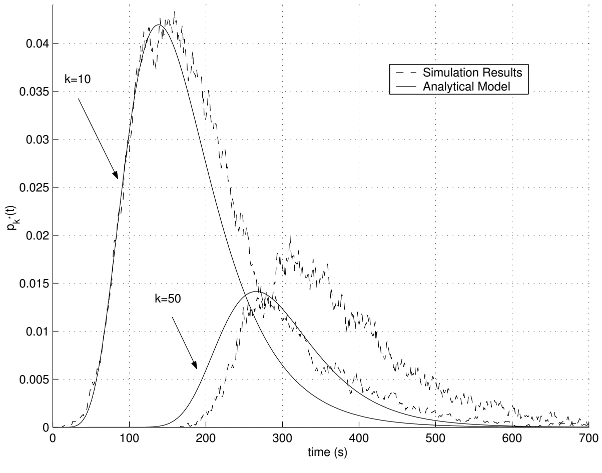



Fig. 6. Probability distribution of state $k = 10, 50$ in the case of 100 mobile users moving according to a Random Waypoint Mobility Model, $v = 4$ m/s, $R = 50$ m .

In Fig. 7, the probability mass function of the number of message copies in the network at time instants $t = 10, 100, 300$ is plotted in the case of 100 U-Nodes. The analytical framework is numerically evaluated and compared with the outcome of 10000 simulations. Also this graph confirms a good correspondence between simulation results and the proposed analytical framework for low values of time $t$ and state $k$.

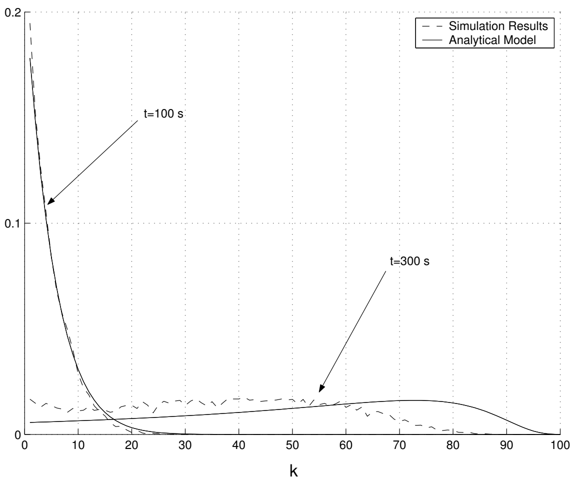



Fig. 7. Probability mass function of the number of message copies in the network at time instants $t^* = 100, 300$, in the case of 100 mobile users moving according to a Random Waypoint Mobility Model, $v = 4$ m/s, $R = 50$ m .

In Fig. 8, we compared the average number of message copies in the network, obtained with the analytical results presented in Sec. III-A, together with the fluid-flow approximation (30) and the simulation outcomes in the case of 100 U-Nodes. The graph shows how both (30) and the analytical framework, while being approximations, significantly represent the number of message copies in the network as obtained from the simulation results.

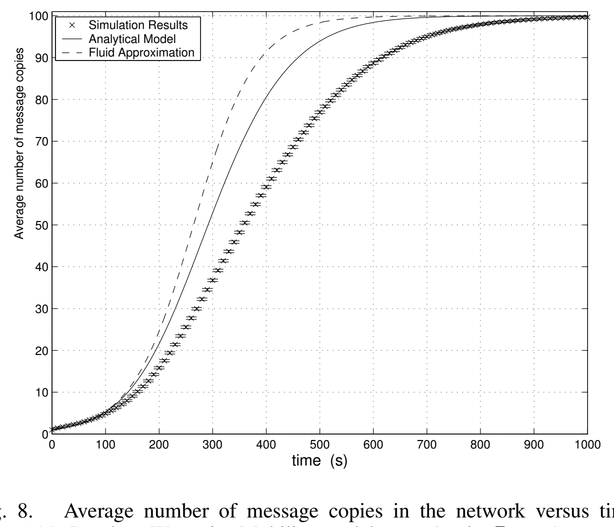



Fig. 8. Average number of message copies in the network versus time, $N = 100$, Random Waypoint Mobility model, $v = 4$ m/s, $R = 50$ m .

Given the sufficient accuracy of the relaying model, we focused on the spatial diffusion of the information in the environment.

[4] Clearly, short time intervals correspond low values of the number $k$ of copies of the message in the network.

In Fig. 9, the approximation of the maximum distance covered by a message in a finite time interval, as defined in (32), is evaluated and plotted together with the results of simulations. The number of U-Nodes is set to 100. The graph shows that the approximation matches well the simulation results for low time values. Starting from $t = 100$ s a discrepancy can be observed between the analytical model and the simulation results. This is the effect of the non-homogeneous stationary distribution of the Random Waypoint Mobility Model. In the stationary regime of RWM, the density of mobile users is higher in the central region of the playground [32]. Therefore, as U-Nodes move toward the area boundaries, the probability of meeting other devices lowers, reducing the relaying probability.

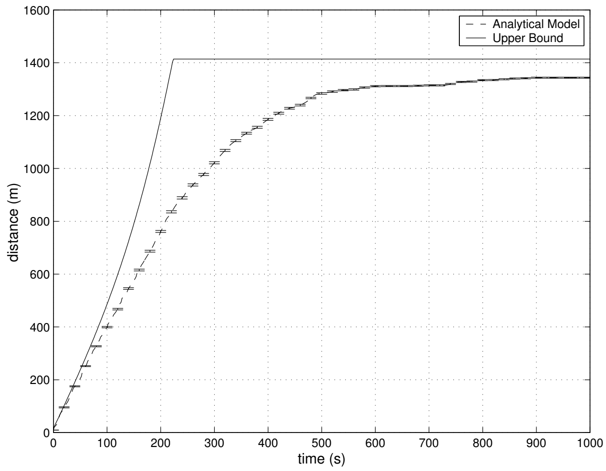
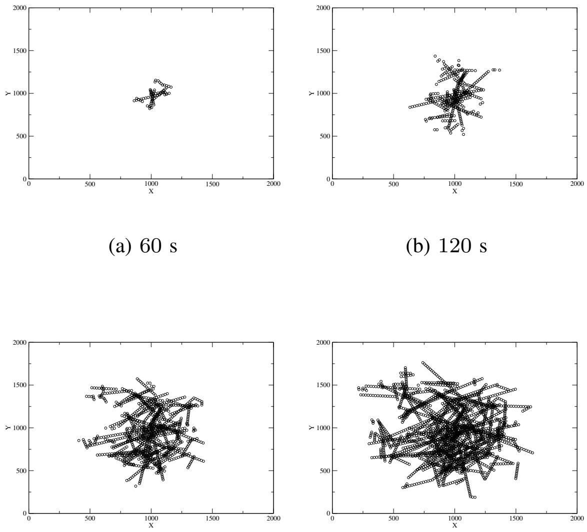



Fig. 9. Approximation vs. simulation results for the distance traveled by a message in the case of 100 mobile users moving according to a Random Waypoint Mobility model, $v = 4$ m/s, $R = 50$ m .

In Fig. 10, we represented the "footprint" (obtained sampling the position of the infected nodes at each second) of the information diffusion in the playground, and provides an intuitive visual representation of the space covered by a message in a limited time interval $(60, 120, 180$ and $240$ seconds, respectively). There is one single sensor, located in the center of the simulation area. Time starts when the sensor is read by one of the 200 U-Nodes. The sensor reading is then propagated in the environment by means of physical movement and relaying to other U-Nodes encountered on-the-move, as described in Sec. II. In Fig. 10 all the positions covered by the users, to which the message has already been delivered, are traced. Each position is traced with a circle of radius equal to 50 m, i.e. the communication range of U-Nodes. The footprint shows that the message diffusion occurs isotropically, not following preferred directions.

Finally, in Fig. 11 the maximum distance covered by a message over time is plotted for different numbers of mobile users $N = 10, 50, 100, 200, 300$. One sensor is initially positioned in the center of the playground and time starts when the sensor is read by a U-Node passing by. Also in this case, simulation starts from the RWM stationary distribution, which enables us to let the first user reading the sensor at time 0, without the need for waiting the transient phase to be over. We have run 50



(a) 60 s (b) 120 s

(c) 180 s (d) 240 s

Fig. 10. Footprint of the information diffusion in the case of 200 mobile users moving with a speed of 4 m/s according to a Random Waypoint Mobility model, after $60, 120, 180$ and $240$ seconds, respectively.

simulations [5] for each considered scenario, with a granularity of 1 s. Clearly, the curve saturates when the maximum possible distance (1414 m) over the $2000 \times 2000$ $m^2$ simulation area is reached. The first part of the graph, i.e. $t$ below 300 sec, is similar for different number of users, except the case of 300 U-Nodes. In this case, the effect of *connected islands* makes the spatial propagation of the message faster. In the second part of the graph, i.e., $t$ above 300 sec, the number of mobile users strongly influence the maximum covered distance, whereas the

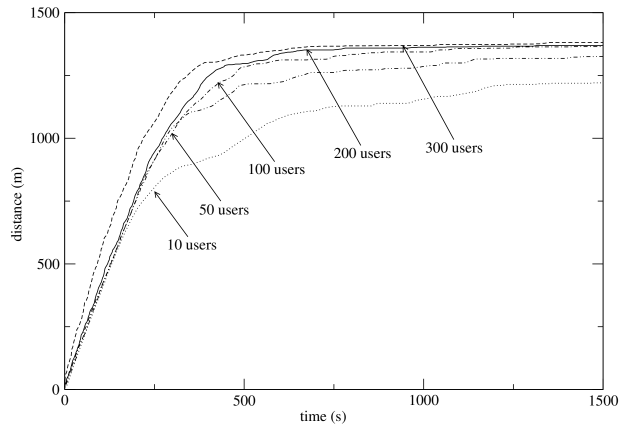



Fig. 11. Maximum covered distance versus time for $N = 10, 50, 100, 200, 300$ with mobile users moving according to a Random Waypoint Mobility Model, $v = 4$ m/s, $R = 50$ m .

[5]In this case there was no need to perform more extensive simulation runs, due to the small size of the confidence interval.

## IV. Conclusions

In this paper, we have presented BIONETS, a novel bio-inspired framework for the provisioning of autonomic services in pervasive communication/computing environments. We identified three main issues (heterogeneity, scalability and complexity) faced by conventional communication paradigms in such application scenarios, and proposed an integrated solution for addressing such issues. From the communication network standpoint, the result is what we call a Service-Oriented Communication System, a simple two-tier network architecture empowered with a relay protocol and an information filtering mechanism.

The SOCS architecture builds upon a disconnected topology and aims at achieving network scalability through the introduction of a communication paradigm based on localized opportunistic interactions among neighboring nodes. Nodes mobility is exploited to convey information among the different islands of connected nodes. Network devices are classified into two broad categories, depending on their logical roles as well as technical features. Small, tiny sensor nodes are envisaged as the medium through which more complex devices (which run services) can gather information about the surrounding environment. Opposite to classical sensor networks approach, no store-and-forward operations are envisaged for sensor nodes, which helps in keeping their cost low and extending network lifetime.

A form of Information Filtering has been introduced to limit the diffusion (in both time and space domains) of the data generated by sensor nodes. The organization of the network into a stable purposeful system is demanded to the services, for which collaborative bio-inspired evolutionary mechanisms have been envisaged [13]. The foundations of the Information Filtering concept have been presented in an information theoretical framework; a simple stochastic model for the diffusion of information over SOCS has been presented and analyzed. The soundness of the proposed model has been validated through comparisons with the outcomes of extensive numerical simulations.

Two research directions appear of major interest for future studies. The first one concerns the study of evolutionary mechanism for the execution of network management tasks, able to preserve the network stability and organize it into an efficient system. The second one is related to the algorithmic implementation of the Information Filtering paradigm. While in this paper we have limited ourselves to a simple "step-like" approximation of the optimal data rate curve, more complex approaches are needed in order to enhance the system performance in terms of scalability, robustness and efficiency.

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