

Performance evaluation of wireless sensor networks for event-detection with shadowing-induced radio irregularities

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Abstract. In this paper, we study a particular application of wireless sensor networks for event-detection and tracking. In this kind of application, the transport of data is simplified, and guaranteeing a minimum number of packets at the monitoring node is the only constraint on the performance of the sensor network. This minimum number of packets is called event-reliability. Contrary to other studies on the subject, here we consider the behavior of such a network in presence of a realistic radio model, such as the shadowing of the radio signal. With this setting, we extend our previous analysis of the event-reliability approach for the transport of data. In particular, both regular and random networks are considered. The contribute of this work is to show via simulations that, in the presence of randomness or irregularities in the radio channel, the event-reliability can be jeopardized, that is the constraint on the minimum number of packets at the sink node could not be satisfied.

1. Introduction

A Wireless Sensor Network (WSN) is a wireless network where the nodes are sensors, that is micro-devices with limited computation capacity and with on-board specific transducers. The applications of such networks are habitat monitoring, structural analysis of buildings, security, target tracking and localization [1,2]. The limited computational capability and energy resources of sensor nodes are the main differences between WSN and other wireless networks such as the cellular networks. The size of sensor nodes can be of few centimeters [3]. Consequently, the algorithms embedded within sensors should be energy efficient and also computational efficient. Other distinctive aspects of WSNs are the communication reliability and congestion control. One cannot afford to use the same reliable transports used in other data networks, as the TCP. Besides other reasons, one which refrains to use such transport protocols is that, in traditional data nets, one reasonably supposes that communication paths are stable along the transmission instances. This fact permits to use the end-to-end approach for the design of reliable transport and application protocols. The TCP works well because of the stability of links. On

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the other hand, in WSNs communication paths, i.e. sequences of wireless links, can change over time, because of time-varying characteristics of links and nodes reliability. The variability of wireless links impacts on the quality of the transmission. In general, the causes of this variability are several, such as the hardware differences among sensors, the energy variance of batteries, or the impairments of the radio medium.¹ As a consequence, many routing protocols and application algorithms should take into account link irregularities, as stated also in [5,6]. In this paper, as a case study, we study a particular application of WSNs for event-detection and tracking. The application is based on the assumption that WSNs present some degree of spatial redundancy. For instance, whenever an event happens, a certain number of sensor nodes, higher than that strictly required, will detect the event and transmit event data to the Monitoring Node (MN). Because of the spatial redundancy, we can tolerate some packet loss, as long as the required detection or event-reliability holds. This reliability can be formulated as the minimum number of packets required by the MN in order to re-construct the event field. An interesting consequence of this application is that we can use a simple connection-less transport of data. The rate of the transmitted data depends on many factors, as the bound on the signal distortion perceived at the MN [7]. In the case of discrete event in the form of “event present” or “event not present”, this scheme resembles the packet repetition scheme.

The novelty of our study is that we assume the radio medium is affected by randomness, for instance the shadowing or log-normal model. Accordingly, in the context of event-detection, we perform the analysis of the system by focusing on the Packet Delivery Ratio (PDR) perceived at the MN, which can be considered as an estimate of the event-reliability. We make the assumption that the application must detect the event within a fixed time window. This parameter depends on the application. For example, in mobile object tracking, the detection window depends on the speed of the object. We do not address the exact tuning of this parameter, i.e. the detection interval, because it is out of the scope of the paper. However, we choose the same value used in other works in order to have a fair comparison. The higher the PDR is, the higher is the reliability of the network in detecting the event.

To the best knowledge of the authors the radio links irregularities have not taken into account in previous research on WSNs simulations for even-detection. Only the work in [8] addressed the same technique, but in that work the effects of the irregularities of the radio model have not been considered. We will show how the irregularity of the radio medium affects the performance of the event-detection approach. Although in absence or in a low-variance shadowing scenario, this study can be of some interest, because the same effect of the shadowing can be rooted in the variation of battery power as stated also in [6], which is present in WSNs. In our previous work, we considered only grid or regular networks [9]. Here, we extend the investigation also to random networks. Based on the results of this work, we argue that ad-hoc routing and MAC protocols should be carefully engineered in order to accommodate the requirements of the WSNs applications. Furthermore, the density and the transmission range of sensors should be set by taking into account the asymmetry of radio links. For a review of the state-of-the art see [10,12].

The paper is organized as follows. In Sections 2 and 3, we explain the model of the WSN under test and the event detection/transport technique, respectively. In Section 4, we discuss the simulation results. Conclusions of the paper are given in Section 5.

¹Many radio models can be found in the classical book of Rappaport [4].

2. WSN model

In our WSN, every node detects the physical phenomenon and sends back to the MN data packets. We suppose that the MN is more powerful than sensor nodes. This model can be considered as a model for remote monitoring of hazard or inaccessible areas [13]. We analyze the performance of the network in a fixed time interval, τ . This can be considered as the available time for the detection of the phenomenon and its value is application dependent. In these simulations, we arbitrarily set $\tau = 30$ s.

Topology For the physical layout of the WSN, two types of deployment can be used: the random and the lattice deployment. In the former, nodes are supposed to be uniformly distributed inside the service area, while in the latter nodes are vertexes of particular geometric shape, e.g. a square grid. For lattice networks, we should set the transmission range, r_0 , of every node to the step size, d in order to guarantee the connectedness of the network.² In fact, by this way the number of links that every node can establishes with neighboring nodes, a.k.a the node degree, is $D = 4$, if we do not count the nodes at the borders, which have $D = 2$ or $D = 3$. It is worth noting that for the network connectedness, by using Cooper's theorem [14] along with some power control techniques, also $D = 2$ suffices.³ The settings of our lattice are shown in Table 1. The sensing range is assumed to be half of the transmission range.

In the case of random network, the setting of the transmission range is a little bit more complicated. In fact, since the position of nodes in the plane is a random variable, the number of neighboring links of a node is a random variable as well. First, we recall the following simple result borrowed from the random graph theory.

Definition 1. Let $G(V, E)$ be the graph representation of the network, where V is the set of vertexes and E is the set of links. The network is said to be k -connected iff for every $(u, v) \in V$ there are k disjoint paths connecting u and v . The probability of k -connectivity is $P(1 - \text{conn})$.

Theorem 1. Let suppose that nodes, or vertexes of $G(V, E)$ are uniformly distributed in the unitary Euclidean plane with intensity ρ . Asymptotically, the probability of connected network converges to 1 if the transmission range r_0 of every node is set as follows:

$$r_0 \geq \sqrt{\frac{\ln\left(\frac{\ln(P(1-\text{conn}))}{-\rho}\right)}{-\rho\pi}}, \quad (1)$$

where $P(1 - \text{conn})$ is the 1-connectivity probability.

The transmission range r_0 is the distance for which the received power is greater than a specific threshold. This threshold depends on the hardware, e.g. modulation and coding schemes, noise floor. We will use Eq. (1) in Section 2.

The network is supposed to have a single sink. In the lattice network, the MN is located at the top-right corner of the lattice. This situation is not far from the reality, because in some habitat monitoring applications, like the observation of mountains slope with landslide dangers, the sink could not be placed otherwise. However, in random networks, we let the MN to occupy any position in the plane.

Sensor Node and Phenomenon Model In order to simulate the detection of a natural event, we used the libraries from Naval Research Laboratory (NRL) [15]. In this framework, a phenomenon is modeled

²The step size is the minimum distance between two rows (or columns) of the grid.

³By using the theorem in [14], we can say that a simple 2-regular network is almost surely strongly 2-connected.

as a wireless mobile node. The phenomenon node broadcasts packets with a tunable synchrony or pulse rate, which represents the period of occurrence of a generic event.⁴ These libraries provide the sensor node with an alarm variable. The alarm variable is a timer variable: It turns off the sensor if no event is sensed within an alarm interval. In addition to the sensing capabilities, every sensor can establish a multi-hop communication towards the MN by means of a particular routing protocol. This case is the opposite of the polling. We used two kind of reactive protocols: the Ad-hoc On Demand distance Vector (AODV) and the Dynamic Source Routing (DSR) [16]. Although not optimal for multi-hops WSNs, we assume that the MAC protocol is the IEEE 802.11 standard. These protocols are not optimal for sensor networks, because they are conceived for ad-hoc multi-hop networks, where the data duty cycle and the energy resources are higher than in WSNs. However, we use them as reference for other comparisons. The receiver of every sensor node is supposed to receive correctly data bits if the received power exceeds the receiver threshold, γ . This threshold depends on the hardware.⁵ As reference, we select parameters values according to the features of a commercial device (MICA2 OEM). In particular, for this device, we found that for a carrier frequency of $f = 916$ MHz and a data rate of 34 KBaud, we have a threshold (or receiver sensitivity) $\gamma|_{dB} = -118$ dBm [3]. The calculation of the phenomenon range is not yet optimized, and for now the phenomenon propagation is assumed to follows the propagation laws of the radio signals. In particular, the emitted power of the phenomenon is calculated according to a two-rays propagation model [4].

Radio Model and Transmission Power Two main phenomena affect the received power at a certain distance. The first one is the free space propagation of electromagnetic waves. These in turn can be reflected by surrounding objects and terrain as well, and in general are attenuated with the distance according to a power law relation. The second one accounts for the fact that surrounding clutters may be different at two different locations, and then the received power is in general different even if the transmitter-receiver separation is constant. It is the so called shadowing or large-scale path loss, in contrast with its counterpart, the small-scale path loss or fading which accounts for impairments due to time-frequency variations of the radio channel [4]. Early measurements within real sensor net testbeds demonstrated that these variations are of concern. However, the right model of the radio randomness strongly depends on the radio environment as well as the transmitter characteristics [17].

Here, we use the shadowing model for the radio medium. The shadowing model assumes that the received power at the sensor node is:

$$P_r(d)|_{dB} = \underbrace{P_t|_{dB} - \beta_0 - 10\alpha \log\left(\frac{d}{d_0}\right)}_{\text{deterministic part}} + \underbrace{S_{dB}}_{\text{random part}} \quad (2)$$

where β_0 is a constant. The term S_{dB} is a random variable, which accounts for random variations of the path loss. This variable is also known as log-normal shadowing, because it is supposed to be Gaussian distributed with zero mean and variance σ_{dB}^2 , that is $S_{dB} \sim \mathcal{N}(0, \sigma_{dB}^2)$. Given two nodes, if $P_r > \gamma$, where γ is the hardware-dependent threshold, the link can be established. The case of $\sigma = 0$, $\alpha = 4$, $d > d_0$ is also called the Two-Ray-Ground model and it is a deterministic model.

⁴As a consequence, this model is for discrete events. By setting a suitable value for the pulse rate, it is possible in turn to simulate the continuous signal detection such as temperature or pressure.

⁵Other MAC factors affect the reception process, for example the Carrier Sensing Threshold (CST) and Capture Threshold (CP) of IEEE.802.11 used in ns-2.

Lattice Network As said in Section 2, $D = 2$ guarantees a connected network.⁶ Thus, it suffices to guarantee a value of $Prob(D \geq 2)$ as close as possible to 1. To this aim, let us note that the link between any two nodes is a bernoullian random variable with a certain probability p . If we consider only the closest neighbors, we have that $Prob(D \geq 2) \geq \sum_{2 \leq k \leq 4} \binom{N}{k} p^k (1-p)^{N-k}$. For $p = 0.95$, $Prob(D \geq 2) \approx 0.9995$. Thus, based on the grid step d and on Eq. (2), we can set the maximum transmission range by solving $p = Prob\{P_r(d)|_{dB} > \gamma|_{dB}\} = 0.95$. It is straightforward to show that:

$$P_t(d)|_{dB} = \left[10\alpha \log_{10} d + \gamma|_{dB} - \text{erfc}^{-1}(2p)\sqrt{(2)\sigma} \right] + \beta_0, \quad (3)$$

where erfc^{-1} is the inverse of the standard error function. This formula provides the transmission power of each sensor, given a transmission range and a probability or rate of coverage p . This should not be confused with the sensing coverage of the WSN. An obvious effect of the shadowing is the random coverage of the transmission range of each sensor. We will have different received powers in different directions. Consequently, the real coverage radius is not constant as in the ideal isotropic radiation case.

Random Networks In the case of random networks, we suppose that the coordinates in the Euclidean plane of every sensor are random variables uniformly distributed in the interval $[0, L] \times [0, L]$. The Eq. (1) is valid for networks where the radio model is deterministic, i.e. the received power is as in Eq. (2), with $\sigma_{dB}^2 = 0$. To take into account the shadowing effects, we shall modify the formula of the transmission range. It can be shown that a similar expression holds [18–21]. In particular, by giving the following definition,

$$\zeta \triangleq \left(\frac{\ln(10)\sigma}{10\alpha} \right)^2, \quad (4)$$

we have that the transmission range is:

$$r_0 \geq \sqrt{\frac{\ln\left(\frac{\ln P(\text{conn})}{-\rho A}\right)}{-\pi \rho e^{2\zeta}}}, \quad (5)$$

where A is the physical area of the network. The formula Eq. (5) makes use of the fact that the distribution of nodes in the plane is a 2-dimensional Poisson process with intensity ρA . However, given the equality of variance and mean in the Poisson process, we use this formula also for the uniform distribution of nodes. Accordingly, the transmission power is set as:

$$P_t = \gamma \beta_0 r_0^\alpha,$$

where r_0 is computed by using, respectively, (1) for the deterministic case (i.e. Two-Ray-Ground model) and Eq. (5) for the shadowing case. However, we will use Eq. (5) also for the deterministic case. In this way, in absence of shadowing, the level of interference depends on the transmission range and

⁶It is worth noting that this condition does not consider the quality of an individual link, generally measured by the Signal-to-Noise Ratio (SNR) and/or the Bit Error Probability (BER). In other words, from a communication point of view, two nodes can be inside their radio range, but the BER can be very low. This means that the BER does not correlate with the distance. The reason of this fact is that in WSN the background noise, the multipath propagation, the imperfections of hardware and the variance of battery power cannot be neglected. Here, we assume that the packet losses are caused by the shared access to the radio medium by several nodes.

Table 1
Topology settings

LATTICE	
step (m)	$d = \frac{L}{\sqrt{N}-1}$
service area size (m ²)	$L^2 = (800 \times 800)$
number of nodes	$N \in \{16, 64, 256\}$
transmission range (m)	$r_0 = d$
RANDOM	
density (nodes/m ²)	$\rho \in \{25 \cdot 10^{-6}, 2 \cdot 10^{-4}\}$
transmission range (m)	$r_0 = 180$

Table 2
Radio model and system parameters

RADIO MODEL PARAMETERS	
path loss coefficient	$\alpha = 2.7$
variance	$\sigma_{dB}^2(\text{dB}) = 16$
carrier frequency (MHz)	916
antenna	omni
threshold (sensitivity) (dB)	$\gamma = -118$
OTHER PARAMETERS	
reporting frequency (pps)	$T_r = [0.1, 1000]^1$
interface queue size (packets)	50
UDP packet size (bytes)	100
detection interval (s) τ	30

¹packet per seconds.

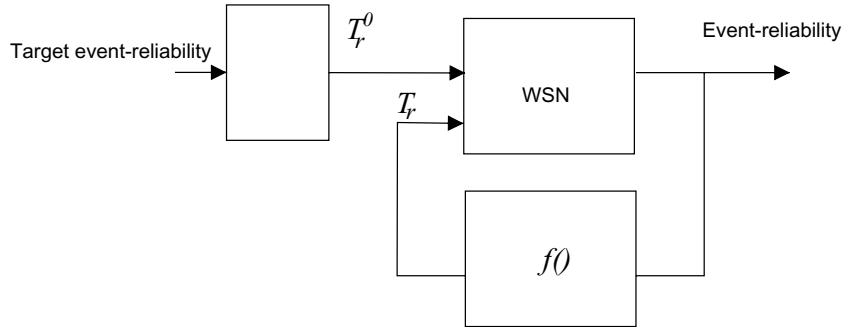


Fig. 1. Representation of the transport based on the event-reliability.

can be considered fairly equal in both cases. Moreover, to be more conservative, we compute r_0 for the lowest ρ only. For example, for $\rho = 25 \cdot 10^{-6}$ nodes/m² and $P(1 - conn) = 0.4$, we have $r_0 = 180$ m, as shown also in Table 1. Then, we use the same r_0 also for $\rho > 25 \cdot 10^{-6}$. It is worth noting that $P(1 - conn) = 0.4$ is enough to guarantee on average a “practically” connected network, i.e. then number of sensor nodes which are isolated can be neglected. The radio model parameters are listed in Table 2.

Interference In general, in every wireless network the electromagnetic interference of neighboring nodes is always present. The interference power decreases the Signal-to-Noise Ratio (SNR) at the intended receiver, which will perceive a lower bit and/or packet error probability. Given a particular node, the interference power depends on how many nodes are transmitting at the same time of the a given node. In a WSN, since the number of concurrent transmissions is low because of the low duty-cycle of sensors,

we can neglect the interference. In other words, if we define duty-cycle as the fraction between the total time of all transmissions of sensor data and the total operational time of the net, we get always a value less than 0.5. In fact, the load of each sensor is $\ll 1$ because sensors transmit data only when an event is detected [22]. However, it is intuitive that in a more realistic scenario, where many phenomena trigger many events, the traffic load can be higher, and then the interference will worsen the performance with respect to that we study here. Consequently, we can fairly say that the results we get here should be considered as an upper bound on the system performance with respect to more realistic scenarios.

3. Event detection and transport

Here, we use the data-centric model similar to [7], where the end-to-end reliability is transformed into a bounded signal distortion concept. In this model, after sensing an event, every sensor node sends sensed data towards the MN. The transport used is a UDP-like transport, i.e. there is not any guarantee on the delivery of the data. While this approach reduces the complexity of the transport protocol and well fit the energy and computational constraints of sensor nodes, the event-reliability can be guaranteed to some extent because of the spatial redundancy, as explained also in Section 1. The sensor node transmits data packets reporting the details of the detected event at a certain transmission rate.⁷ The setting of this parameter, T_r , depends on several factors, as the quantization step of sensors, the type of phenomenon, and the desired level of distortion perceived at the MN. In paper [7], the authors used this T_r as a control parameter of the overall system. For example, if we refer to event-reliability as the minimum number of packets required at MN in order to reliably detect the event, then whenever the MN receives a number of packets less than the event-reliability, it can instruct sensor nodes to use a higher T_r . This instruction is piggy-backed in dedicated packets from the MN. This system can be considered as a control system, as shown in Fig. 1, with the target event-reliability as input variable and the actual event-reliability as output parameter. The target event-reliability is transformed into an initial T_r^0 . The control loop has the output event-reliability as input, and on the basis of a particular non-linear function $f(\cdot)$, T_r is accordingly changed. We do not implement the entire control system, but only a simplified version of it. For instance, we vary T_r and observe the behavior of the system in terms of the mean number of received packets. In other words, we open the control loop and analyze the forward chain only.

4. Simulations

In this Section, we present the simulation results of our WSN. We simulated an ad-hoc network by means of NS-2 simulator, with the support of NRL libraries.⁸ Accordingly, we use for our purposes the PDR metric, which is the maximum of the event-reliability. The PDR is defined at the MN, and it is the received packet rate divided by the sent packets rate. Thus:

$$G(\tau) = \frac{N_r(\tau)}{N_s(\tau)}, \quad (6)$$

⁷Note that in the case of discrete event, this scheme is a simple packet repetition scheme.

⁸Since the number of scheduler events within a simulated WSN can be very high, we applied a patch against the scheduler module of NS-2 in order to speed up the simulation time [23].

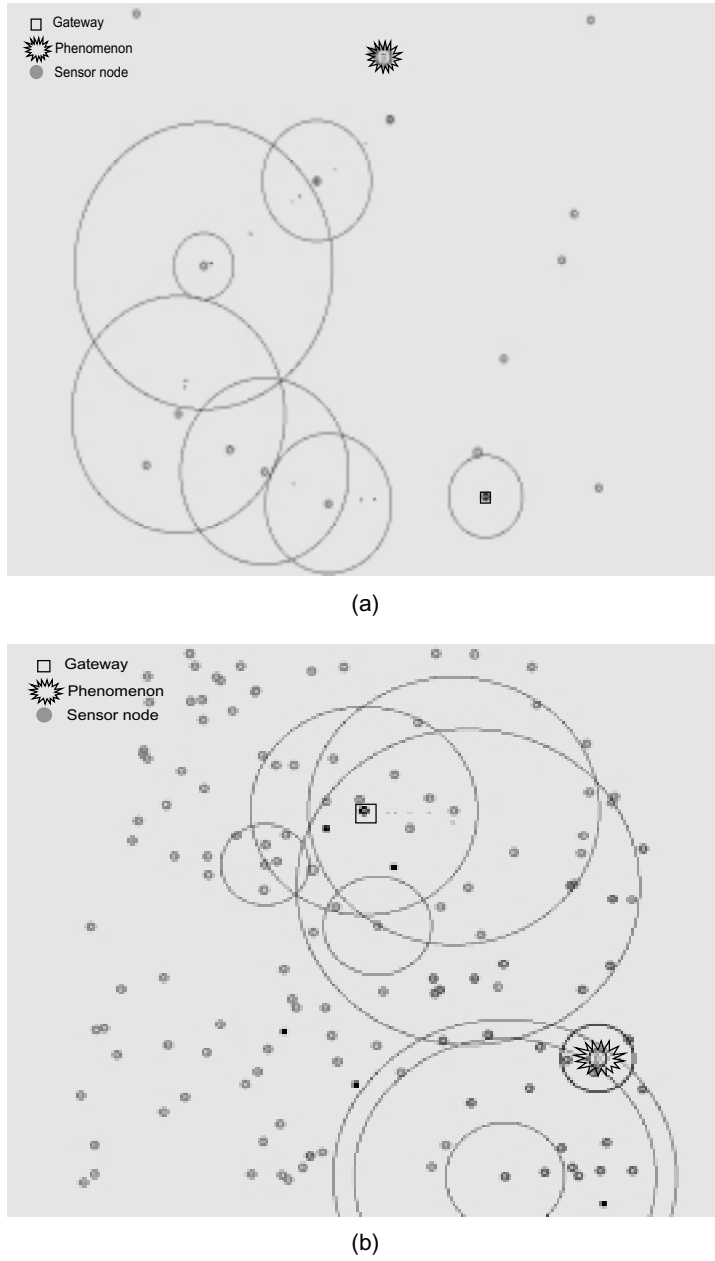


Fig. 2. Example of realization of random network, in a) $\rho = 25 \cdot 10^{-6}$ and in b) $\rho = 2 \cdot 10^{-4}$.

where $N_r(\tau)$ is the number of received packet at the sink, and the $N_s(\tau)$ is the number of packets sent by sensor nodes which detected the phenomenon. These quantities are computed in a time interval of τ seconds. Note that the event-reliability is defined as $G_R = \frac{N_r(\tau)}{R(\tau)}$, where R is the required number of packets or data in a time interval of τ seconds. In general, we have $G_R(\tau) \geq G(\tau)$. The initial position of phenomenon node is varied along the simulation runs, except the case of random network. In fact, in the random network, there are three sources of randomness: the position of nodes, the position of the

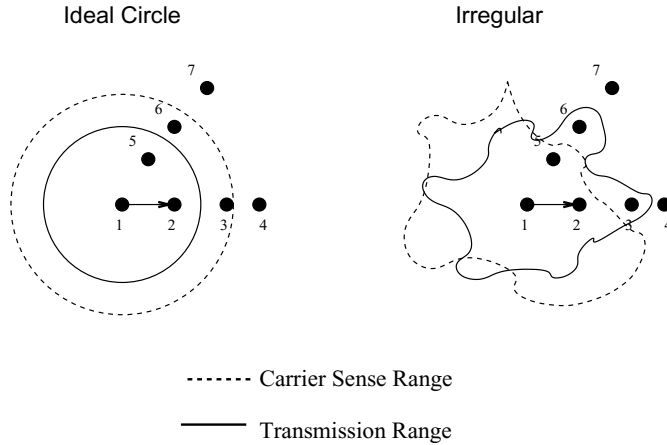


Fig. 3. Illustration of the hidden node problem.

MN and, in presence of shadowing, the received power. Therefore, we keep fixed the position of the phenomenon while the position of nodes changes at every run. Snapshots of random networks generated in simulations are shown in Fig. 2.

Lattice Network For each routing protocol, the sample averages of Eq. (6) are computed over 20 simulation runs, and they are plotted in Fig. 4(a)(b), with respect to the particular radio model used. We also show the 95% confidence interval of the sample averages. The perceived PDR is a decreasing function of T_r , because as T_r increases, the capacity of the WSN limits the maximum number of packets per unit of time which can be injected in. We can clearly distinguish three operating zones. For low values of T_r , the network is uncongested (just 30 data packets). At a particular value of T_r (~ 10 pps), the PDR drops abruptly, because the network has reached the maximum capacity. For $T_r > 10$ pps, contention and congestion periods augment, increasing T_r does not ameliorate the PDR and $N_r(\tau)$ is roughly constant. Although these three zones are present regardless of the radio model, in the case of shadowing the PDR decreases with N , as shown in the right parts of Fig. 4.

The explanation of this effect is not simple, because it is intermingled with the dynamics of MAC and routing protocol. However, intuitively we can say that in the case of shadowing the on-demand routing protocols are affected by the presence of shadowing-induced unidirectional links. It is worth noting that AODV and DSR cannot use unidirectional links. On the other hand, exploiting such links is possible but the performance gains are quite low. Thus, the routing protocol spends most of the time in the searching of a bi-directional path. Thus, given a fixed detection interval, N_r can be much lower than its value in the case of ideal radio model, i.e. the Two-Ray-Ground model, where the discovered paths do not change over time.⁹ This fact may or may not affect the performance of the WSN, because it depends on the requirements of the application.

For high values of N , the augmented interference level and the path instability seem to be predominant. In fact, as shown in Fig. 5, the average delay towards the MN increases. For instance, it is 50% higher with respect to the Two-Ray-Ground case. The main cause of such disparity between the two cases is the path asymmetry, i.e. the path from a node towards the MN does not coincide with the reverse path. The path asymmetry in turn can be caused by an increased number of hidden/exposed nodes [24]. The hidden

⁹This is true if we do not count the reliability of nodes, i.e. the probability of failure of sensor nodes.

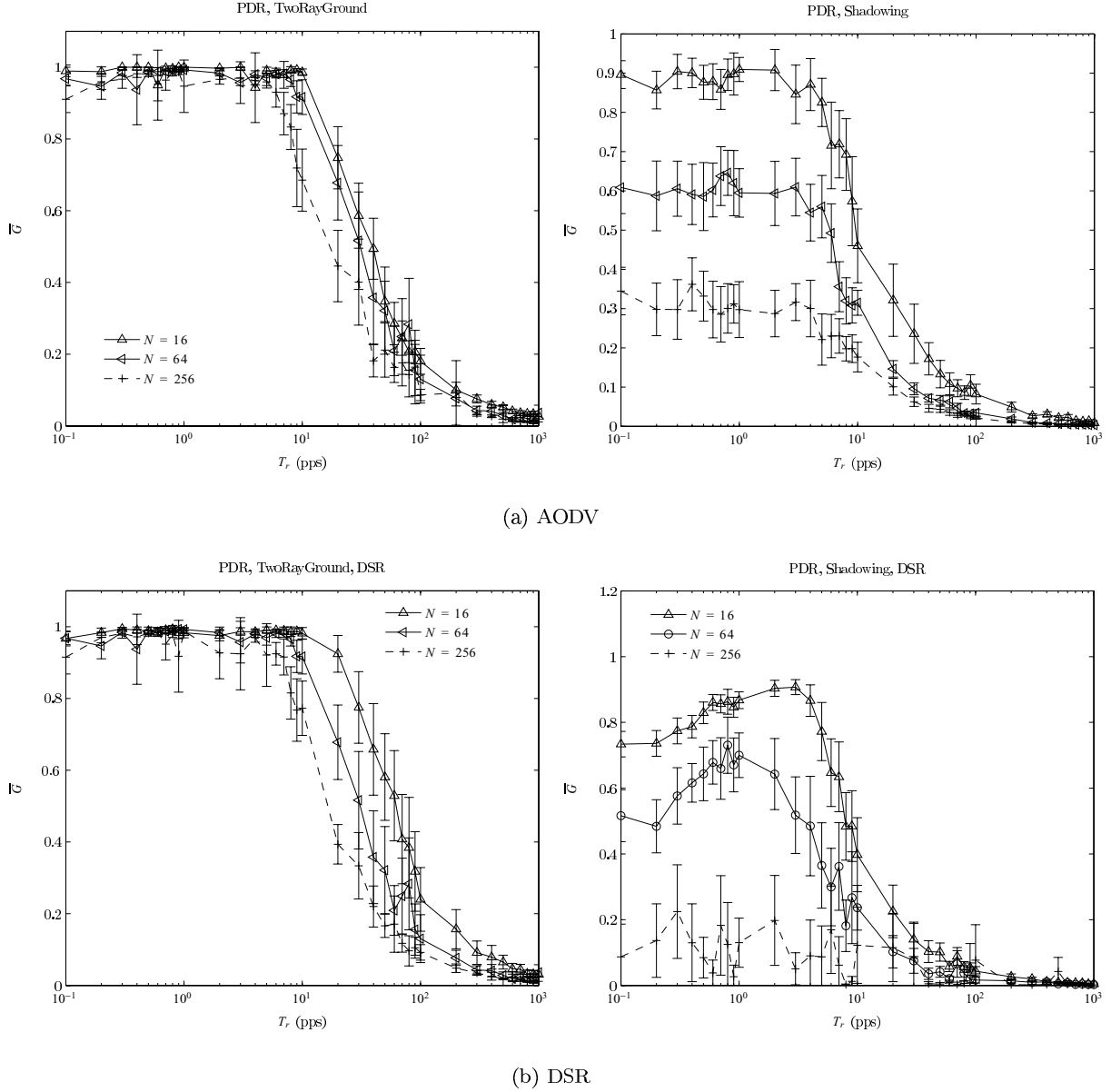


Fig. 4. Sample averages of the PDR.

node problem is well known in CSMA networks. It arises when the a node is not in the Carrier Sense (CS) range of another node. Therefore, a collision will happen if distant nodes start a transmission. We give an example in Fig. 3. If we assume an ideal circle for the CS range, nodes 7 and 4 are hidden and might cause collisions at node 2. If we assume an irregular shape for the CS range, the hidden nodes are 3, 4 and 7.

We can confirm this fact in the following way. In Fig. 6, we report the routing efficiency, that is:

$$\eta_R \triangleq \frac{N_s(\tau)}{N_{RO}(\tau)} \leq \frac{\tau T_r}{N_{RO}(\tau)}$$

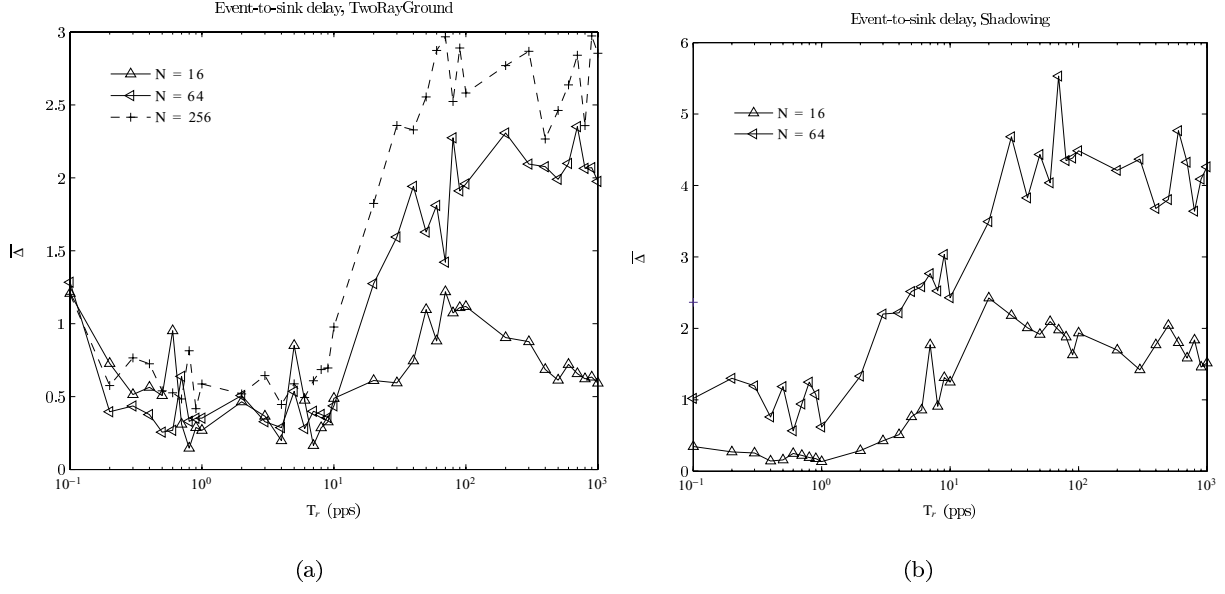


Fig. 5. Average delay for AODV.

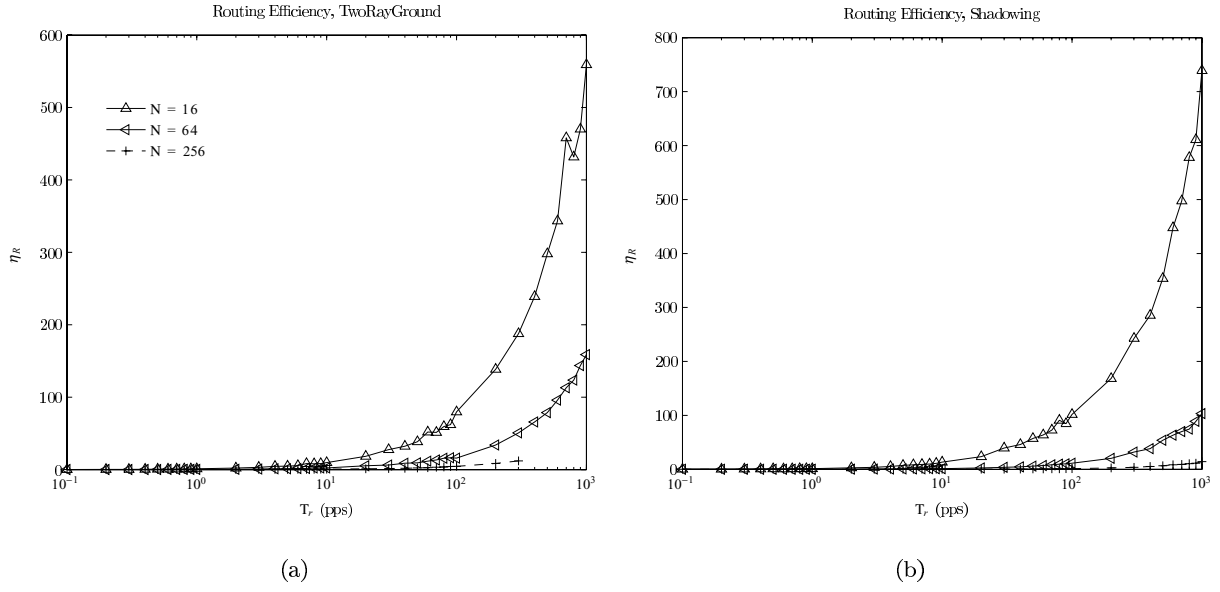


Fig. 6. Average routing efficiency for AODV.

where $N_{RO}(\tau)$ is the number of routing packets in τ . This figure tell us that the routing overhead is roughly the same (we did not show the confidence interval for sake of clarity).

However, if we look at the number of losses of packets carrying UDP data, i.e. after the contention resolution procedure of the MAC protocol, we can clearly see that in the presence of shadowing this number increases. However, as N increases, there is a strange effect for which the number of losses decreases with N . The reason of this fact can be found in the following explanations. In general, the

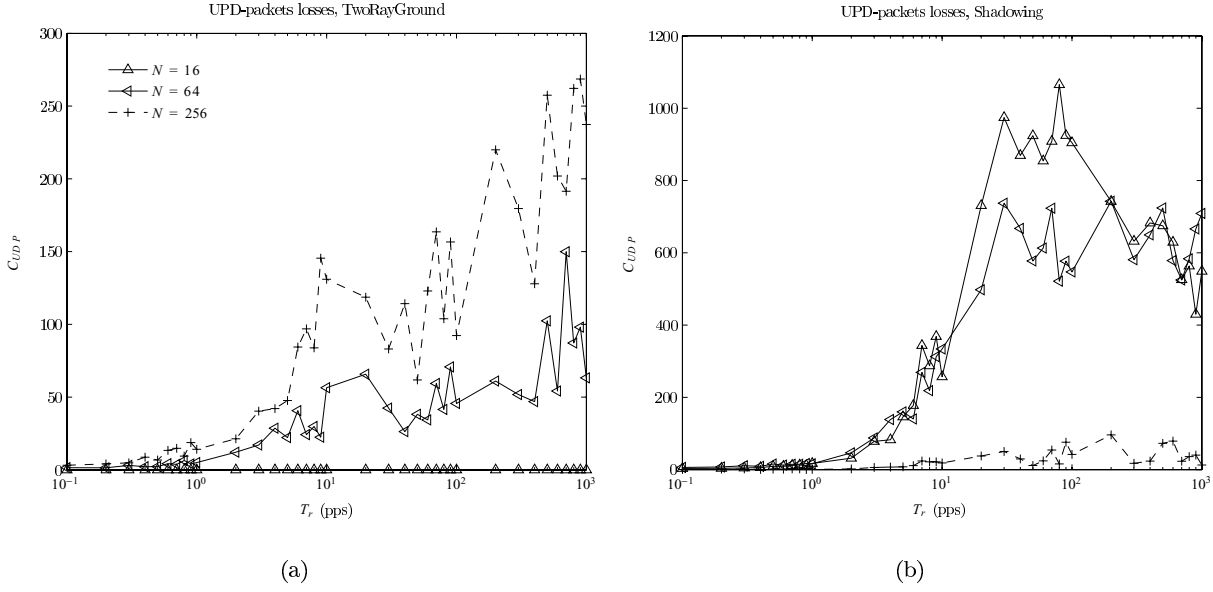


Fig. 7. Average number of MAC/UDP collisions.

MAC losses are confined within the transmitting range or coverage of a node. If the MAC layer does not receive any acknowledgment from the receiver, it retransmits packets by following the back-off mechanism, up to a timeout time, after which the packet is considered lost. If the coverage is constant, the number of losses within the network will be roughly proportional to the network size. This is confirmed by Fig. 7-a. In the case of shadowing, Fig. 7-b, the coverage is not uniform, and collisions to non-neighboring nodes can happen. Moreover, in NS-2 the shadowing is considered time-varying, i.e. at every packet transmission the path loss is re-computed. Hence, the coverage is also time-varying. Although a time-varying shadowing might appear unrealistic, the same result arises if we consider other more abstract models, such as the Cerpa's model [25]. The occurrence of this phenomenon increases with T_r . However, after $N = 16$, the number of collisions decreases, either because every node is silenced by an increased number of neighboring nodes, due to the shadowing, and because fewer UDP packets are sent. Consequently, in the former case, nodes will defer the transmission of packets more frequently, by inducing less collisions as overall effect. Since the maximum number of collisions is still higher than that in the case of Two-Ray-Ground model, this kind of losses affects the delay remarkably, as shown in Fig. 5-b. Note also that in the case of $N = 256$ in Fig. 5-b, we did not show any data, because the number of samples is not enough to draw any statistical evaluation. In this case, the values of the event-to-sink delay span the entire $[0, 10]$ s range. This means that most of time, when the MN receives packets, most of the delays are high. Although we did not analyze it in this work, another aspect which affects the PDR is the network InterFace Queue length (IFQ) of nodes. The higher is the number of sensor nodes which send event data, the higher is the load at every sensor nodes which act as relay. Therefore, if IFQ is "too short", many packets will be lost and the routing overhead will increase. On the other hand, if the IFQ is "too long", the event-to-sink delay might increase at the point that more timeouts will be fired at the routing layer. Note also that DSR performs worse than AODV, for low values of T_r and τ .

If all nodes had a constant sensing range, and not proportional to the transmission range as we assumed, the higher is the node density, the higher will be the number of nodes which can detect the phenomenon and the congestion level inside the network.

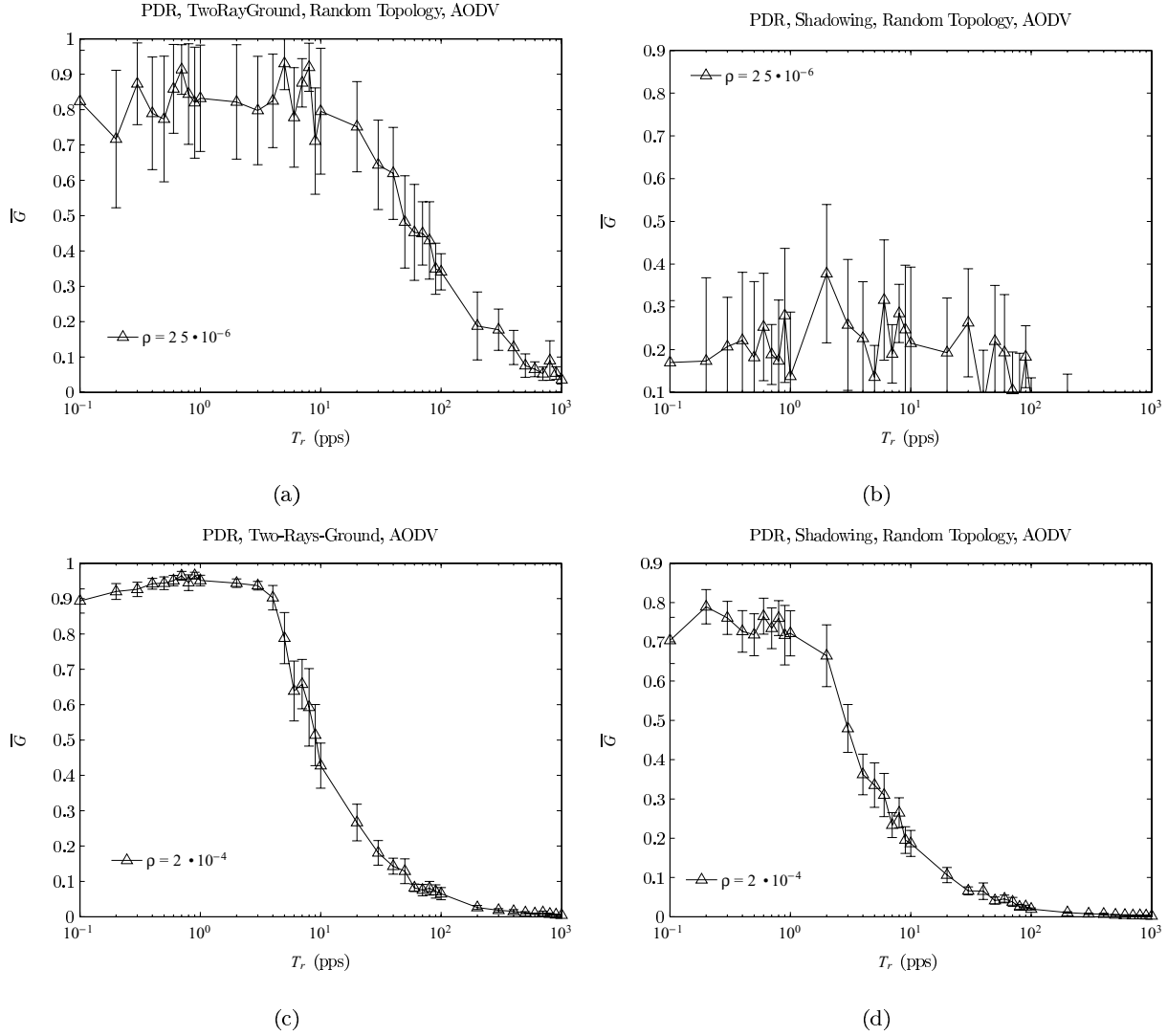


Fig. 8. PDR for random topologies, $\rho = 25 \cdot 10^{-6}$ nodes/m² in (a)(b), and $\rho = 2 \cdot 10^{-4}$ nodes/m² in (c)(d).

Random Networks Similarly to the above discussion, we have the same results also for random networks, as shown in Fig. 8. In this case, the variances of the PDR are higher than those in the previous case, because there are two sources of randomness. In the case of the Two-Ray-Model, they are the position of the MN and the number of neighboring nodes. In the case of shadowing, there is also the path loss variation. The position of the MN impacts on the PDR, because it can be happen that the MN is in a place near the phenomenon or in a place where few nodes are present. In the former case, the number of received packets is intuitively higher, because retransmissions and collisions are reduced. The same happens in the latter case, where the contention for the channel is due to a reduced number of nodes. The opposite case also arises, as shown in 8-(a)(b). In particular, as shown in Fig. 8-(b), the shadowing is another cause of randomness, and the PDR decreases, as in the previous type of network. In Fig. 8-(c)(d), we show the PDR for $\rho = 2 \cdot 10^4$ nodes/m². In this case, the WSN with shadowing has a higher PDR, but not higher than the Two-Ray-Ground PDR. The increased density reduces the probability of isolated

MNs and one of the randomness source is shaded.

5. Conclusions

In this paper, we presented our simulation results of a WSN, with a single sink and fed by a number of sensors nodes which detect a generic physical event. It is well known that received power at sensor nodes is not isotropic in real-life environments. However, what is missing in most of the works on the subject is the impact of this fact on the performance of the applications running on top of WSN-based systems. The objective of the paper has been to quantify this impact, although in qualitative way. For instance, we considered the log-normal shadowing as the model for the path loss of radio signals. Even if in the absence of strong (= high variance) shadowing, this model can still be useful, because the variation of the received power can be caused also by the variation of battery power of transmitters. As application of the WSN, we considered the detection of an event in a particular area of the network, e.g. the movement of an object. Because of the spatial redundancy of the network, the transport of event-data can be simplified. In particular, we assumed a connectionless transport of the event data. The performance metric of this application is the number of received packets per time unit, normalized to the number of required packets. To simplify, we used the PDR.

Because of the shadowing, we emphasized the fact that the PDR cannot be arbitrary high regardless of the detection interval τ . In other words, the system has a time factor which is dictated by the routing and MAC protocols. By analyzing in details the loss process, we found that the problems of the CSMA based MAC protocols used in a multi-hop context are stronger. The shadowing is more deleterious at the MAC layer. For random networks, we also emphasized that well-known formula for setting the density of a WSN should take into account the link asymmetry caused by shadowing, which directly impacts on the PDR. It is worth noting that although the values in Eqs (3) and (2) guarantee a connected network, the interference level inside the network could be high, especially in the case of multiple or very close phenomena. The interference in turn directly impacts on the MAC layer and on the average time to set up a connection towards the sink.

To contrast the effect of channel impairments in terms of PDR within a time window τ , a possible solution could be the MN diversity. That is, deploying more than one MN in the network and programming the sensor nodes such that event data are sent to both MNs. This mechanism should be optimized by considering also the power consumption. We will investigate this mechanism in further studies. We are planning to extend the results to other routing and MAC protocols, and evaluate this framework in real-test bed as well.

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References

- [1] *Design and Implementation of Wireless Sensor Networks for Habitat Monitoring*, technical report, J.P. Polastre, <http://www.polastre.com/papers/masters.pdf>.

- [2] B. Sinopoli, C. Sharp, L. Schenato, S. Schaffert and S. Shankar, Distributed Control Applications Within Sensor Networks, *IEEE Proceedings* **91**(8) (August 2003), 1235–1246.
- [3] Crossbow Technology, Inc., <http://www.xbow.com/>.
- [4] T.S. Rappaport, *Wireless Communications*, Prentice Hall PTR, 2001.
- [5] G. Zhou, T. He, S. Krishnamurthy and J. A. Stankovic, Models and solutions for radio irregularity in wireless sensor networks, *ACM Transaction on Sensors Network* **2**(2) (2006), 221–262.
- [6] M. Zuniga and B. Krishnamachari, An Analysis of Unreliability and Asymmetry in Low-Power Wireless Links, <http://www-scf.usc.edu/~marcozun/>, 2006.
- [7] Özgür B. Akan and I.F. Akyildiz, Event-to-Sink Reliable Transport in Wireless Sensor Networks, *IEEE/ACM Transactions on Networking* **13**(5) (2005), 1003–1016.
- [8] M.C. Vuran, V.C. Gungor and O.B. Akan, On the Interdependency of Congestion and Contention in Wireless Sensor Networks, in: *Proceedings of CST SenMetrics '05*, July, 2005, <http://users.ece.gatech.edu/mcvuran/Interdep-SenMetrics.pdf>.
- [9] T. Yang, G. De Marco, M. Ikeda and L. Barolli, A Case Study of Event Detection in Lattice Wireless Sensor Network with Shadowing-Induced Radio Irregularities, in: *Proceedings of The Fourth International Conference on Advances in Mobile Computing & Multimedia (MoMM)*, 2007, pp. 241–250.
- [10] S. Giordano and C. Rosenberg, Topics in ad hoc and sensor networks, *IEEE Communication Magazine* **44**(4) (2006), 97–97.
- [11] J.N. Al-Karaki and A.E. Kamal, Routing Techniques in Wireless Sensor Networks: A Survey, *IEEE Wireless Communication* **11**(6) (December 2004), 6–28.
- [12] G. De Marco, M. Longo and F. Postiglione, Connectivity of Ad Hoc Networks with Link Asymmetries Induced by Shadowing, *IEEE Communication Letter* (2007).
- [13] G.W. Allen, K. Lorincz, O. Marcillo, J. Johnson, M. Ruiz and J. Lees, Deploying a Wireless Sensor Network on an Active Volcano, *IEEE Internet Computing* **10**(2) (March 2006), 18–25.
- [14] C. Cooper, A note on the connectivity of 2-regular digraphs, *Random Structures Algorithms* **4** (1993), 469–472.
- [15] I. Donward, NRL's Sensor Network Extension to NS-2, <http://pf.itd.nrl.navy.mil/nrlsensorsim/>.
- [16] C.E. Perkins, ed., *Ad Hoc Networks*, Addison-Wesley, 2001.
- [17] W.M. Merrill, H.L.N. Liu, J. Leong, K. Sohrabi and G. Pottie, Quantifying Short-Range Surface-to-Surface Communications Links, *IEEE Antennas and Propagation Magazine* **46**(3) (2004), 36–46.
- [18] G. De Marco, M. Longo and F. Postiglione, Connectivity of Ad Hoc Networks with Link Asymmetries Induced by Shadowing, *IEEE Communication Letter* (2007).
- [19] C. Bettstetter, Failure-Resilient Ad Hoc and Sensor Networks in a Shadow Fading Environment, *Proceedings IEEE/IFIP Intern. Conf. on Dependable Systems and Networks (DSN), Workshop on Dependability Issues in Wireless Ad Hoc Networks and Sensor Networks (DIWANS)*, June 2004, 900.
- [20] R. Hekmat and P. Van Mieghem, Study of Connectivity in Wireless Ad-Hoc Networks with an Improved Radio Model, *Proceedings of the Second Workshop on Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks (WiOpt'04)*, 2004, 142–151.
- [21] D. Miorandi and E. Altman, Coverage and Connectivity of Ad Hoc Networks in Presence of Channel Randomness, *Proceedings of IEEE INFOCOM 2005* **1** (2005), 491–502.
- [22] W. Ye, J. Heidemann and D. Estrin, Medium access control with coordinated adaptive sleeping for wireless sensor networks, *IEEE/ACM Transaction Networking* **12**(3) (2004), 493–506.
- [23] D.X. Wei, Speeding up NS-2 scheduler, California Institute of Technology, <http://netlab.caltech.edu/~weixl/technical/ns2patch>.
- [24] P.C. Ng and S.C. Liew, Throughput Analysis of IEEE 802.11 Multi-hop Ad hoc Networks, *IEEE/ACM Transaction on Networking* (June 2007).
- [25] A. Cerpa, J.L. Wong, L. Kuang, M. Potkonjak and D. Estrin, Statistical model of lossy links in wireless sensor networks, *Proceeding of Fourth International Symposium on Information Processing in Sensor Networks*, 2005, 2005, 81–88.

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