



On network connectivity of wireless sensor networks for sandstorm monitoring

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ABSTRACT

As serious natural disasters, sandstorms have caused massive damages to the natural environment, national economy, and human health in the Middle East, Northern Africa, and Northern China. To avoid such damages, wireless sensor networks (WSNs) can be deployed in the regions where sandstorms generally originate so that sensor nodes can collaboratively monitor the origin and development of sandstorms. Despite the potential advantages, the deployment of WSNs in the vicinity of sandstorms faces many unique challenges, such as the temporally buried sensors and increased path loss during sandstorms. Consequently, the WSNs may experience frequent disconnections during the sandstorms. In this paper, the connectivity issue of WSNs for sandstorm monitoring is studied. First, four types of channels a sensor can utilize during sandstorms are analyzed, which include air-to-air channel, air-to-sand channel, sand-to-air channel, and sand-to-sand channel. Based on these analytical results, the percolation-based connectivity analysis is performed. It is shown that if the sensors are buried in shallow depth, allowing sensor to use multiple types of channels improves network connectivity. Accordingly, much smaller sensor density is required compared to the case, where only terrestrial air channels are used. Through this connectivity analysis, a WSN architecture can be established for efficient and effective sandstorm monitoring.

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1. Introduction

Sandstorms cause massive damages to the natural environment, national economy, and human health in the Middle East, Northern Africa, and Northern China. Among these damages, sandstorms play an important role in the spread of diseases by blowing virus spores on the ground into the atmosphere. In addition, the significantly reduced

visibility interrupts aircraft and road transportation. Sandstorms also cause forced dust injection, which greatly damages human respiratory system. These serious consequences necessitate effective sandstorm forecasting systems to provide timely and accurate sandstorm warnings.

Nowadays, several sandstorm forecasting systems have been deployed to serve different regions and countries. These systems include Asian Dust Aerosol Model (ADAM) system [11], Mediterranean Dust Regional Atmospheric Model (DREAM) system [10], and Chinese Unified Atmospheric Chemistry Environment for Dust (CUACE) system [6]. These existing systems, however, face challenges in providing accurate sandstorm forecasting because they lack real-time observation capabilities from the sandstorm sources, such as relative humidity, maximum surface

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winds, and maximum temperature. More specifically, the currently operational forecasting systems, such as CUACE [6], heavily rely on meteorological stations to collect and transmit the meteorological and geographic information. However, meteorological stations have to be deployed in the potential sand source regions to provide real-time environment monitoring. Such a strategy is not feasible in certain areas such as Middle East, where the deserts are the main origins of sandstorms. In addition, due to their high deployment cost, the density of existing meteorological stations is not sufficient to yield an acceptable coverage for accurately locating the regions where sandstorms originate.

To address these challenges, in situ coverage of sandstorms is required using low-cost monitoring devices. To this end, wireless sensor networks provide a promising solution to realize real-time environment monitoring, large-area coverage, on-site data processing, and rapid information delivery [2]. Specifically, WSNs can be easily deployed by dropping the ground sensors from a plane so that sensors are quickly and efficiently placed in a large target area. To prevent the deployed sensors flying away during sandstorms, each sensor is tied to an anchor. After a wireless sensor network is deployed, the networked sensors can collaboratively collect real-time meteorological and dust information such as atmospheric pressure, temperature, humidity, wind speed, and soil moisture status. The gathered information is then preprocessed, aggregated/compressed, and transmitted to a remote control center, where sophisticated forecasting models can utilize this information to initiate corresponding sandstorm warnings.

Despite the promising aspects of WSNs in sandstorms, there are still many open research issues remaining to be resolved for practical implementation. One of the major issues is how to effectively deploy WSNs under the impact of sandstorms. More specifically, it has been reported that during sandstorms, terrestrial air channels can exhibit an additional path loss of 10–26 dB [5], which implies the reduced transmission range of sensor nodes. In addition, due to the dynamically changing wind field, the sensor nodes can be temporarily buried in the sands, which implies the reduced node density of WSNs. The above two facts indicate that the WSN may experience frequent disconnections during the sandstorms even through good connectivity is guaranteed when the network is initially deployed. To encounter this problem, we allow sensors to use four types of channels based on the locations of the transmitters and receivers, including air-to-air (AA) channel, air-to-sand (AS) channel, sand-to-air (SA) channel, and sand-to-sand (SS) channel [13,14]. By such channel diversity/variability, sensor nodes can connect to the remote sink through multi-hop paths as long as at each hop along a path there exists at least one type channel available.

Although such communication scheme has potential advantages, the connectivity analysis of such scheme is complicated due to the coexistence of multiple types of channels. To solve this problem, we investigate the connectivity issue from the percolation perspective [9]. Percolation theory concerns a phase transition phenomenon where the network exhibits fundamentally different

behavior when the node density λ is below or above the critical density λ_c . If $\lambda > \lambda_c$, the network contains an extremely large connected component such that each node in this component can communicate with each other. In this case, the network is considered to be connected. If $\lambda < \lambda_c$, the network is partitioned into small fragments, and thus becomes unconnected and unusable. Percolation theory has been proven to be a very useful tool for the analysis of large-scale wireless networks [4,8].

In this paper, we first provide the analytical results of the path loss of the four types of channels. Based on the path loss analysis, the transmission range of each channel is derived, which completely depends on the environmental conditions. Then, we prove that there also exists a critical density λ_c^{Multi} for the WSNs under the impact of sandstorms. It is shown that λ_c^{Multi} is a function of the wind dynamics of sandstorms and the transmission ranges of multiple types of channels. Accordingly, we demonstrate that when sensors are buried in shallow depth, λ_c^{Multi} is smaller than λ_c^{AA} , the critical density of the single medium communication scheme, which only uses terrestrial air channels. This implies that jointly using multiple types of channels improves network connectivity. Accordingly, smaller node density is required for achieving the same connectivity performance as the single medium case, i.e., only air-to-air communication.

The rest of this paper is organized as follows. Section 2 introduces the network architecture. Section 3 presents channel models in sandstorms. In Section 4, we present the topology analysis based on percolation theory. Finally, Section 5 concludes this paper.

2. Network architecture

To acquire the real time and comprehensive measurements of the sand source, in a WSN, a great number of unattended ground sensors are deployed in the vast desert area, as shown in Fig. 1. The humidity, temperature, soil moisture, and wind speed/direction of the desert are measured by those sensors. The measurements of each sensor are then transmitted in a multi-hop fashion to a data sink. The data sink collects the sensing reports from the sensors and detects possible sandstorms by fusing the sensing reports. Then, the data sink forwards the detection reports to the remote administration center through satellite links.

In the harsh environmental conditions of the desert, the sensors can be temporarily buried by sands frequently due to the wind dynamics. Consequently, the wireless communication between sensors can be severely affected and the network connectivity is degraded. To mitigate the impacts of sandstorms on network connectivity, we employ multiple types of channels in sandstorm monitoring. Specifically, under such communication paradigm, the sensor nodes that are temporarily buried in the sands still maintain their communication abilities but with smaller transmission ranges. Based on the locations of the transmitters and receivers, four types of channels are utilized, including air-to-air (AA) channel, air-to-sand (AS) channel, sand-to-air (SA) channel, and sand-to-sand (SS) channel, as shown in Fig. 2 [13,14]. Then, two sensor nodes (either

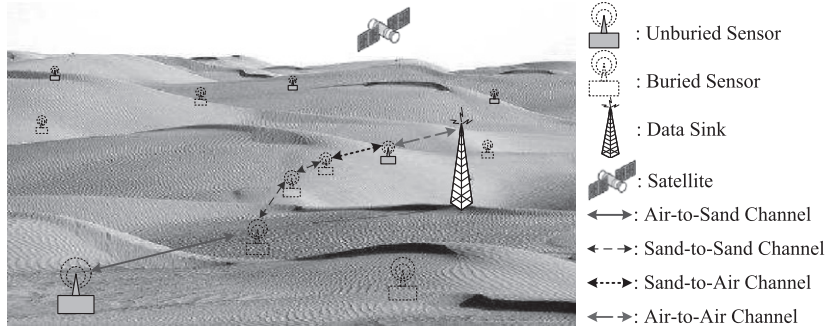


Fig. 1. Network architecture.

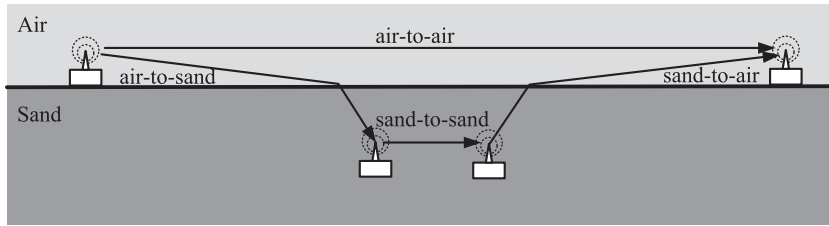


Fig. 2. Communication scheme with multiple channel types.

buried in sand or unburied) can be connected through multi-hop relays, where the relay sensor nodes can also be either buried in sand or unburied. As a result, the impact of the sandstorms on the network connectivity can be effectively mitigated.

3. Channel models

In spite of the potential advantages, the connectivity of such wireless sensor networks is complicated due to the existing of four types of channels. The communication ranges of the four types of channels are different and are highly dynamic as the changes of environmental conditions. In the rest of this subsection, we calculate the path loss of the four types of channels as functions of the environmental conditions. Then, the communication ranges can be derived based on the path loss. Since the wireless communications in sands can be viewed as a special case of the underground communications [1], the following channel analysis is based on our previous analysis on the wireless underground channel characteristics [16,15].

3.1. Air-to-air channel

In [5], it has been pointed out that the sandstorm can cause an additional path loss of 10–26 dB that for duration of several minutes. Therefore, the path loss of the air-to-air channel L_{AA} can be calculated using the Friss equation:

$$L_{AA}(d_{air}) = -147.6 + 20 \log d_{air} + 20 \log f + L_{sandstorm}, \quad (1)$$

where d_{air} is the length of the air path; f is the operating frequency; $L_{sandstorm}$ is the additional path loss caused by the sandstorm that is in the range of 10–26 dB.

3.2. Sand-to-sand channel

If $L_{sand}(d)$ is the signal loss of an sand path with length d_{sand} (meters), then

$$L_{sand}(d_{sand}) = 6.4 + 20 \log d + 20 \log \beta + 8.69 \alpha d_{sand}, \quad (2)$$

where α is the attenuation constant whose unit is $1/m$, and β is the phase shifting constant whose unit is $radian/m$. The values of α and β depend on the dielectric properties of sand:

$$\alpha = 2\pi f \sqrt{\frac{\mu\epsilon'}{2} \left[\sqrt{1 + \left(\frac{\epsilon''}{\epsilon'}\right)^2} - 1 \right]}, \quad (3)$$

$$\beta = 2\pi f \sqrt{\frac{\mu\epsilon'}{2} \left[\sqrt{1 + \left(\frac{\epsilon''}{\epsilon'}\right)^2} + 1 \right]}, \quad (4)$$

where f is the operating frequency, μ is the magnetic permeability, ϵ' and ϵ'' are the real and imaginary parts of the relative dielectric constant of the sand. ϵ' and ϵ'' are functions of the sand properties, which include the volumetric water content (VWC), the bulk density, and the composition of the sand.

Since the sensors are buried near the air-to-sand interface, the reflection from the air-to-sand interface needs to be considered, as shown in Fig. 3. If the burial depth of sensors is h_u , the total path loss of the sand-to-sand channel L_{UG-UG} is deduced as

$$L_{SS}(d_{sand}) = L_{sand}(d_{sand}) - 10 \log V(d_{sand}, h_u), \quad (5)$$

where $V(d, h)$ is the attenuation factor due to the second path:

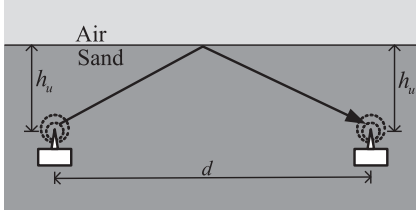


Fig. 3. Illustration of the sand-to-sand channel.

$$V^2(d_{sand}) = 1 + (\Gamma \cdot \exp(-\alpha\Delta r))^2 - 2\Gamma \exp(-\alpha\Delta r) \times \cos\left(\pi - \left(\phi - \frac{2\pi f}{c\sqrt{\epsilon'}}\Delta r\right)\right), \quad (6)$$

where Γ and ϕ are the amplitude and phase angle of the reflection coefficient at the reflection point, c is the velocity of light in vacuum, and $\Delta r = \sqrt{d_{sand}^2/4 + h_u^2} - d_{sand}$, is the difference of the two paths.

3.3. Sand-to-air channel

The path loss of the sand-to-air channel L_{SA} consists of three parts: the sand path loss L_{sand} , the air path loss L_{AA} and the refraction loss from sand to air L_{S-A}^R :

$$L_{SA}(d_{sand}, d_{air}) = L_{sand}(d_{sand}) + L_{AA}(d_{air}) + L_{S-A}^R, \quad (7)$$

where d_{sand} is the length of the sand path, and the d_{air} is the length of the air path, as shown in Fig. 4(a). The sand path loss L_{sand} and air path loss L_{AA} can be derived from (2) and (1), respectively.

Since the dielectric constant of sand is much larger than the air, the signals with an incident angle θ_I that is larger than the critical angle θ_c will be completely reflected. Moreover, because the length of the air path d_{air} is much larger than the height of the sensor antenna h_a , the incident angle θ_I is approximately equal to θ_c ; and the refracted angle θ_R is approximately equal to 90° , as shown in Fig. 4(a). Then the horizontal distance d between the buried sensor and unburied sensor is approximately equal to d_{air} . And

$$d_{sand} \approx \frac{h_u}{\cos\theta_c}; \quad \theta_c \approx \arcsin\frac{1}{\sqrt{\epsilon'}}. \quad (8)$$

The refraction loss L_{S-A}^R can be calculated as:

$$L_{S-A}^R \approx 10 \log \frac{(\sqrt{\epsilon'} + 1)^2}{4\sqrt{\epsilon'}}. \quad (9)$$

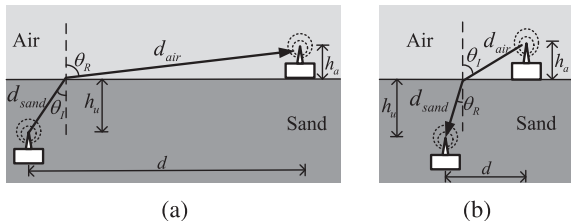


Fig. 4. Illustration of (a) sand-to-air channel and (b) air-to-sand channel.

3.4. Air-to-sand channel

Similar to the sand-to-air channel, the path loss of the air-to-sand channel is:

$$L_{AS}(d_{sand}, d_{air}) = L_{sand}(d_{sand}) + L_{AA}(d_{air}) + L_{A-S}^R, \quad (10)$$

where L_{A-S}^R is the refraction loss from air to sand. As shown in Fig. 4(b), because the dielectric constant of sand is much larger than the air, most radiation energy from the unburied sensors will be reflected back if the incident angle θ_I is large. Therefore, we only consider the signal with small incident angle. Consequently, the refracted angle θ_R in the soil is even smaller hence it can be viewed approximately as zero. Then the sand path length $d_{sand} \approx h_u$, and the horizontal distance d between the buried sensor and the unburied sensor is:

$$d \approx \sqrt{d_{air}^2 - h_a^2}, \quad \cos\theta_I = \frac{h_a}{d_{air}}. \quad (11)$$

The refraction loss L_{A-S}^R can be calculated as

$$L_{A-S}^R \approx 10 \log \frac{(\cos\theta_I + \sqrt{\epsilon' - \sin^2\theta_I})^2}{4\cos\theta_I\sqrt{\epsilon' - \sin^2\theta_I}}. \quad (12)$$

3.5. Transmission ranges of the four types of channels

We set the transmit power of the sensor as P_t , and the antenna gains of the receiver and transmitter as g_r and g_t , respectively. Then the received power, $P_r(d)$, at a receiver sensor node d meters away is $P_r(d) = P_t + g_r + g_t - L_{path}(d)$, where $L_{path}(d)$ is the corresponding path loss calculated either by (1), (5), (7), or (10). Then the corresponding transmission range of the channel can be calculated as

$$R = \max\{d : P_r(d)/P_n > SNR_{th}\}, \quad (13)$$

where P_n is the noise power; and SNR_{th} is the minimum signal-to-noise ratio required by the receiver.

In next section, we denote the transmission ranges of air-to-air channel, sand-to-sand channel, sand-to-air channel, and air-to-sand channel as R_{aa} , R_{ss} , R_{sa} , and R_{as} to denote, respectively. The analysis in this section indicates that, due to the high path loss in the sand medium, R_{ss} is very limited (no more than 10 m). R_{aa} is the largest (more than 100 m) since the path loss in the air is the smallest. R_{sa} and R_{as} are in the range of 30–70 m, depending on the burial depth and sand property. It should be noted that R_{sa} is larger than R_{as} , since a large portion of signal energy can penetrate the air-to-sand interface from sand to air while most energy is reflected back in the opposite direction. However, this difference becomes smaller when the sensor burial depth decreases [14].

4. Connectivity analysis

4.1. Random geometric graph

To perform the percolation-based topology analysis, We use network geometric graph to model a WSN. In particu-

lar, the sensor nodes are distributed according to homogeneous Poisson point process with density λ . Let $X_{i=0}^n$ denote the locations of sink $\{0\}$ and the nodes $\{1, 2, \dots, n\}$. A communication link exists between two nodes $\{i, j\}$ if their mutual distance, $\|X_i - X_j\|$, is less than the transmission range R so that the SNR at the receiver is sufficiently large for successfully decoding. The graph with all node pairs $\{i, j\}$ with $\|X_i - X_j\| < R$ is called a random geographic graph, denoted by $G(\lambda, r)$.

By continuum percolation theory [9], there exists a critical density $0 < \lambda_c < \infty$ such that if $\lambda > \lambda_c$, there exists an infinite connected component, i.e., a connected component with an infinite number of nodes, in $G(\lambda, R)$. The exact value for λ_c is not known. For the random disk graph with $r = 1$, i.e., $G(\lambda, 1)$, numerical simulations show that $1.43 < \lambda_c^1 < 1.44$ [12].

Different from the conventional terrestrial sensor networks, the ground sensors of a WSN can be temporally buried in the sands caused by the wind dynamics. To model this phenomena, each sensor node is associated with an independent and identically distributed (i.i.d.) alternating renewal process, denoted by $S(t)$, which alternates between two states: the ON state, during which the sensor is exposed on the ground; and the OFF state, during which the sensor is buried in sand. Denote the length of ON and OFF state by $\tau_0 > 0$ and $\tau_1 > 0$, respectively. Assume $\tau_0(\tau_1)$ follows an arbitrary distribution with finite expectation, i.e., $E(\tau_0) < \infty$ and $E(\tau_1) < \infty$. Based on the above assumptions, the marginal distribution of $S(t)$ is given by

$$P_{ex} = \Pr(S(t) = 0) = \frac{E(\tau_0)}{E(\tau_0) + E(\tau_1)},$$

$$P_{bu} = \Pr(S(t) = 1) = \frac{E(\tau_1)}{E(\tau_0) + E(\tau_1)}, \quad (14)$$

where P_{ex} and P_{bu} denotes the probability that at an arbitrary time instance a sensor node stays exposed and buried, respectively. According to the thinning theory of Poisson point process [9], the exposed and buried sensors are still distributed as Poisson point processes with density of $P_{ex}\lambda$ and $P_{bu}\lambda$, respectively.

4.2. Effective transmission range

When sensors are allowed to use multiple types of channels, the buried sensors can act as the relay nodes for the unburied sensors. Therefore, as shown in Fig. 2, a communication link between two unburied sensors consists of three sublinks: air-to-sand (AS) sublink, sand-to-sand (SS) sublink, and sand-to-air (SA) sublink, with length denoted by L_{as} , L_{ss} , and L_{sa} , respectively. Therefore, the effective transmission range R_{eff} can be expressed by

$$R_{eff} = L_{as} + L_{ss} + L_{sa}. \quad (15)$$

The AS and SA sublink is only used for 1-hop connection, i.e., AS sublink connects the unburied source node to a buried relay node, while SA sublink connects a buried relay node to the unburied destination node. Therefore, we have

$$L_{as} = R_{as}, \quad L_{sa} = R_{sa}. \quad (16)$$

In contrary, the SS sublink can be a multi-hop path between two buried nodes that connect the unburied source and destination nodes, respectively. Thus, the length of the SS sublink depend on several factors, including $P_{bu}\lambda$, R_{ss} , R_{sa} , and R_{as} . Intuitively, as $P_{bu}\lambda$ and R_{ss} increase, so does the probability that longer SS sublinks exist. In addition, as R_{sa} and R_{as} increase, so does the probability that such SS sublinks can connect two randomly selected unburied nodes.

To simplify our analysis of L_{ss} , we consider the case where the sensors are buried in shallow depth. According to our channel analysis, this indicates that the sand-to-air and air-to-sand channels are symmetric, i.e.,

$$R_{sa} \approx R_{as}. \quad (17)$$

In this case, applying scaling relation for continuum percolation [3], the SS sublink length is given by

$$L_{ss}(\lambda) = 2k \left(\frac{R_{ss}}{2R_{as} - R_{ss}} \phi \left(\pi \frac{R_{ss}^2}{4} P_{bu}\lambda \right) \right)^\alpha \left(R_{as} - \frac{R_{ss}}{2} \right) \quad (18)$$

and

$$\phi(x) = kx(1 + cx) \left(1 - \frac{4x}{\pi\lambda_c^1} \right)^{-1/2}, \quad (19)$$

where $\alpha = 3/8$, $k = 0.25$, and $c = 2.20$. Combining Eqs. (15), (17), and (18) yields the effective transmission range R_{eff} , i.e.,

$$R_{eff} = 2R_{as} + L_{ss}(\lambda). \quad (20)$$

It is worth to note that although the above equation is derived in the case where sensors are buried in the shallow sands, this equation can serve as a conservative estimate of R_{eff} when the sensors are buried deeply since in this case we have $R_{as} < R_{sa}$, according to our channel analysis.

4.3. Critical density

Based on the derived effective transmission range R_{eff} , we next study the critical density of WSNs. This density λ_c plays a key role in the network deployment phase. If the deployed node density $\lambda > \lambda_c$, then the WSN is connected from the percolation perspective, i.e., there exists an extremely large portion of sensors that can connect to the sink. Otherwise, if $\lambda < \lambda_c$, the WSN would be partitioned into small fragments, and thus becomes unconnected. Next, we derive the critical density λ_c under three cases: pure SS communications, pure AA communications, and communications with multiple types of channels.

4.3.1. Pure SS communications

For pure SS communications, applying the scaling property of continuum percolation, we have the critical density λ_c^{SS} , i.e.,

$$\lambda_c^{SS} = \lambda_c^1 / R_{ss}^2. \quad (21)$$

Obviously, if $\lambda > \lambda_c^{SS}$, the network can keep connected without being affected by the wind dynamics, which are characterized by P_{bu} in Eq. (14). This is due to the fact that the condition $\lambda > \lambda_c^{SS}$ guarantees that even when all sensors

are buried in sands, they can still reach the data sink by multi-hop paths made of short-range SS channels. Since R_{ss} is generally very short, this indicates that extremely high node density is required. Considering its high deployment cost, such scheme is not practical and thus we have $\lambda < \lambda_c^{SS}$.

4.3.2. Pure AA communications

If pure AA channels are utilized to establish connections, at an arbitrary time instance, such channels are only applicable for $(1 - P_{bu})\lambda$ of sensors. Thus, applying thinning theory of Poisson point processes [9], the critical density λ_c^{AA} follows

$$\lambda_c^{AA} = \frac{\lambda_c^1}{R_{aa}^2(1 - P_{bu})}. \quad (22)$$

The above equation indicates that as the probability that a sensor is buried in the sands increases, the sensor nodes have to be deployed in higher density to maintain network connectivity.

4.3.3. Communications with multiple types of channels

In such communication scheme, a pair of nodes is mutually connected if they reside within the effective transmission range R_{eff} of each other. In this case, the critical density λ_c^{Multi} can be derived by solving following equation

$$(1 - P_{bu})\lambda_c^{Multi} = \frac{\lambda_c^1}{(2R_{as} + L_{ss}(\lambda_c^{Multi}))^2}. \quad (23)$$

According to Eq. (18), λ_c^{Multi} is a function in terms of R_{ss} , R_{as} , and P_{bu} , i.e.,

$$\lambda_c^{Multi} = f(R_{ss}, R_{as}, P_{bu}). \quad (24)$$

The analysis above investigates the connectivity issue at a given time instance. To incorporate the wind dynamic process $S(t)$, we apply the similar method as the one used in the proof of dynamic percolation [7] and have the following Theorem.

Theorem 1. Given a WSN $G(\lambda, R_{eff})$ and wind dynamics modeled by alternating renewal process $S(t)$ with $\Pr(S(t) = 1) = P_{bu}$, there exists a critical density $\lambda_c^{Multi} = f(R_{ss}, R_{as}, P_{bu})$ for the communication scheme allowing multiple types of channels, such that if $\lambda > \lambda_c^{Multi}$ then with probability one, there exists an infinite connected component in the $G(\lambda, R_{eff})$ for all times $t > 0$.

Proof. Refer to [7] for details. \square

4.4. Performance evaluation

We now evaluate the network topology by measuring the critical densities. Specifically, we measure λ_c^{Multi} and λ_c^{AA} , respectively, varying the wind dynamic parameter P_{bu} and the buried depth of sensors d . If the measured λ_c^{Multi} is less than λ_c^{AA} , this implies that jointly using multiple type of channels require smaller node density to achieve the same connectivity performance as the single medium

communication scheme, which only uses terrestrial air channels. Other simulation parameters are set as follows: All the transceivers in sensors are the same. The transmitting power is 10 mW at 900 MHz. The minimum received power for correct demodulation is -90 dBm. The antenna gains $g_t = g_r = 5$ dB. The volumetric water content (VWC) in the sand is 1%.

In Fig. 5, λ_c^{Multi} is shown in the case, where the sensors are buried in shallow depth and the burial depth of the sensor's antenna is less than 0.1 m. In this case, by channel analysis in Section 2, R_{as} approximately ranges from 50 m to 70 m, where smaller value is obtained at shallower depth. It can be seen that λ_c^{Multi} decreases as R_{as} increases. This is as expected since larger R_{as} indicates larger R_{eff} and thus smaller λ_c^{Multi} . In addition, we observe that higher P_{bu} leads to larger λ_c^{Multi} . This observation is due to the fact that higher P_{bu} implies more sensors are buried. Accordingly, more sensors have to be deployed to compensate the buried sensors.

In Fig. 6, the ratio of λ_c^{AA} to λ_c^{Multi} , i.e., $r = \lambda_c^{AA} / \lambda_c^{Multi}$, is shown. Specifically, it can be observed that as the R_{as} in-

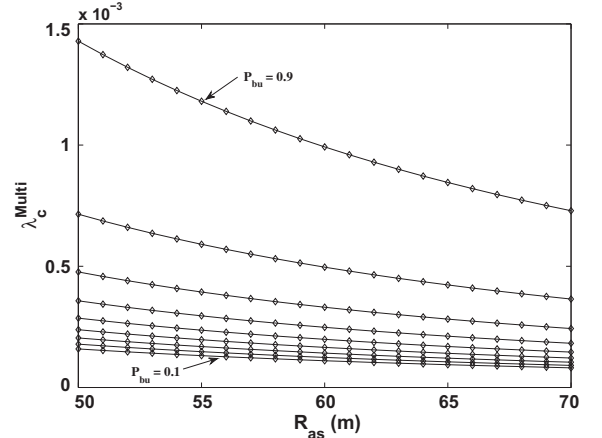


Fig. 5. Critical density based on communication scheme with multiple types of channels.

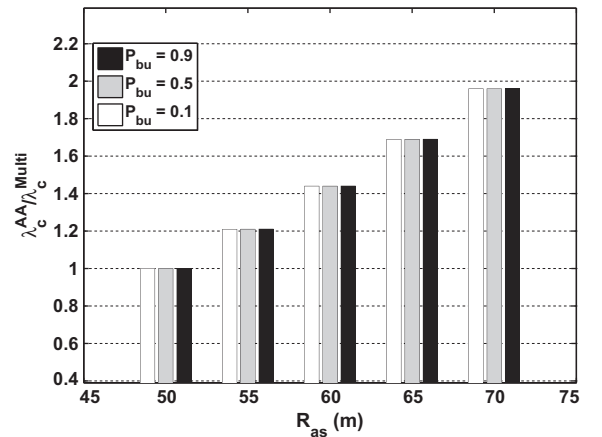


Fig. 6. Critical density ratio of single medium communication scheme and communication scheme with multiple types of channels.

creases, the ratio r increases from 1 to 2. This implies that in the shallow sand case, conventional single medium communication scheme requires more than 2 times the amount of sensors to ensure network connectivity, compared with the scheme which allows the usage of multiple types of channels. In addition, it can be seen that the ratio r remains almost constant as P_{bu} varies from 0.1 to 0.9. This means that the communication scheme which jointly uses multiple types of channels works well in extremely hostile environment such as desert, where a large portion of sensors may be buried as time proceeds.

5. Conclusion

In this paper, we study the connectivity issue of WSNs for sandstorm monitoring. Specifically, the channel characteristics of four types of channels in the sandstorms are introduced. These channels include air-to-air (AA) channel, air-to-sand (AS) channel, sand-to-air (SA) channel, and sand-to-sand (SS) channel. By such channel diversity, the percolation-based connectivity analysis shows that for shallow burial depth, using multiple types of channels improves connectivity. Accordingly, it is shown that smaller sensor density is sufficient to achieve the same connectivity performance compared to the case where only a single communication medium, i.e., terrestrial air channel, is used.

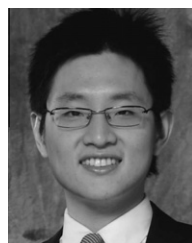
References

- [1] I.F. Akyildiz, E.P. Stuntebeck, Wireless underground sensor networks: research challenges, *Ad Hoc Networks* 4 (6) (2006) 669–686.
- [2] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, Wireless sensor networks: a survey, *Computer Networks Journal* 4 (12) (2002) 393–422.
- [3] A.C. Balram, D. Dhar, Scaling relation for determining the critical threshold for continuum percolation of overlapping discs of two sizes, *Physics and Astronomy (PRAMANA)* 74 (2010) 109–114.
- [4] O. Dousse, F. Baccelli, P. Thiran, Impact of interferences on connectivity of ad hoc networks, *IEEE/ACM Transactions on Networking* 13 (2) (2005) 425–436.
- [5] J. Goldhirsh, Parameter review and assessment of attenuation and backscatter properties associated with dust storms over desert regions in the frequency range of 1–10 GHz, *IEEE Transactions on Antenna and Propagation* 30 (1982) 1121–1127.
- [6] S.L. Gong, X.Y. Zhang, Cuace/dust – an integrated system of observation and modeling systems for operational dust forecasting in Asia, *Atmospheric Chemistry and Physics Discussions* 7 (2007) 10323–10342.
- [7] O. Hggstrm, Y. Peres, J.E. Steif, Dynamic percolation, *Annales de l'Institut Henri Poincaré. Probabilités et Statistiques* 33 (1997) 497–528.
- [8] Z. Kong, E.M. Yeh, A distributed energy management algorithm for large-scale wireless sensor networks, in: *Proc. of ACM MOBIHOC'07*, 2007, pp. 209–218.
- [9] R. Meester, R. Roy, *Continuum Percolation*, first ed., Cambridge University Press, New York, NY, USA, 1996.
- [10] S. Nickovic, G. Kallos, A. Papadopoulos, O. Kalaliagou, A model for prediction of desert dust cycle in the atmosphere, *Journal of Geophysical Research* 106 (2001) 18113–18129.
- [11] S.U. Park, H.-J. In, Parameterization of dust emission for the simulation of the yellow sand (Asian dust) event observed in March 2002 in Korea, *Journal of Geophysical Research* 108 (2003) 4618.
- [12] J. Quintanilla, S. Torquato, R.M. Ziff, Efficient measurement of the percolation threshold for fully penetrable discs, *Physics A* 86 (2000) 399–407.
- [13] A.R. Silva, M.C. Vuran, Empirical evaluation of wireless underground-to-underground communication in wireless underground sensor networks, in: *Proc. of IEEE DCOSS '09*, Marina Del Rey, CA, June 2009.
- [14] A.R. Silva, M.C. Vuran, Communication with aboveground devices in wireless underground sensor networks: an empirical study, in: *Proc. of IEEE ICC '10*, Cape Town, South Africa, May 2010.
- [15] Z. Sun, I.F. Akyildiz, Connectivity in wireless underground sensor networks, in: *Proc. of IEEE SECON 2010*, 2010, pp. 1–9.
- [16] M.C. Vuran, I.F. Akyildiz, Channel modeling and analysis for wireless underground sensor networks in soil medium, *Physical Communication Journal* 3 (4) (2010) 245–254.



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