Mobility Diversity in Mobile Wireless Networks

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***Abstract*—In this paper, we introduce the novel concept of mobility diversity as the diversity gained by transmitting the information of the nodes of a mobile network over different network topologies. Due to the mobility of the nodes, different network topologies emerge which can benefit the information transmission throughout the network. In traditional diversity schemes, such as frequency, time, or spatial diversity, a signal is transmitted over different diversity dimensions (e.g., different frequency bands, different time intervals, or different spatial paths) to combat the destructive effects of fading in each individual channel. In a mobile wireless network, the nodes can exploit the topology diversity to communicate with their corresponding destinations more reliably as compared to the case when the topology of the network is fixed. In fact, in a fixed topology, the probability of a source having a poor connectivity to its destination is higher than the case when there are multiple topologies over which the communication can occur.**

I. Introduction

Diversity schemes refer to methods, used to improve the reliability of information exchange, by using two or more communication channels with preferably independent fading characteristics. Utilizing diversity is an efficient approach to mitigate fading, interference, and noise bursts. The basic idea behind diversity relies in the fact that individual channels are expected to experience *different* (statistically independent) levels of fading or interference. Therefore, while one of the communication channels undergoes deep fading or is exposed to strong interference, it is still likely that the other channels can be used to preserve the integrity of communication. The transmitter, hence, can send multiple copies of the same information over different channels and the respective receiver can combine the corresponding signals to decode the message despite a possible deep fade in individual channels.

Several diversity schemes have been introduced and analyzed in the literature, including time diversity, frequency diversity, spatial diversity, user cooperation diversity, and multiuser diversity. In time (frequency) diversity [1]–[5], multiple copies of the same signal are transmitted at different time instances (over different frequency bands). The time difference (center frequency distance) of adjacent channels should be chosen large enough such that the fading characteristics of individual channels are statistically independent. Spatial diversity can be achieved when the signal is sent over different propagation paths [6]–[9]. In wireless communication, this can be implemented using antenna diversity [10]. Multiple copies of the signal are sent over spatially distanced antennas so that each signal goes through a different path. A very well-established scheme that uses spatial diversity is the so-called multiple input multiple output (MIMO) communication approach, where the transmitter and (or) the receiver are equipped with multiple antennas to establish a communication link [11], [12]. As another form of diversity, user-cooperation diversity has been introduced in the context of cooperative communications, where different nodes share their resources to materialize a distributed MIMO system, thereby helping each other in transmitting and receiving information [13]–[15]. The node which intends to transmit a signal to a destination, first shares its message with the neighboring nodes. Then all the nodes collectively transmit the signal to the respective destination, thereby achieving the so-called user cooperation diversity.

As observed in the aforementioned schemes, diversity is achieved when information is transmitted over statistically independent means of communication. In this paper, we introduce a novel diversity scheme, namely *mobility diversity*. Mobility diversity is herein defined in the context of mobile networks but it can be easily extended to any network with evolving topology which intends to collect information coming from network nodes. A communication scheme is said to be benefiting from mobility diversity if the information generated by the network nodes is collected or transmitted over different network topologies. The change in the network topology is a consequence of the mobility of the network nodes, thus justifying the terminology mobility diversity.

Analogy can be established with the traditional diversity schemes as follows: different communication channels available for signal transmission in traditional diversity schemes are analogous to different topologies of the network. In a certain topology, certain nodes could be isolated from the network or connected to the information collector (sink node) only through many hops, and hence, their data might be lost or experience long delays. Due to nodes' mobility, the network topology is evolving. Thus, in the next emerged topology, those nodes could be in a direct contact with, or a few hops away from a sink node, and therefore, they can communicate their messages easily with acceptable delay or error. Information collected (received) on different topologies are then combined in a fusion center to decode the nodes' messages with a high reliability.

Recently, mobility in wireless sensor networks has been addressed in the literature where different network mobility models are studied and the effect of mobility on the asymptotic performance measures, such as the capacity and delay, has been investigated [16]–[19]. It has been shown that, in an interference channel, mobility can enhance the performance of mobile ad-hoc networks.

In this paper, we introduce the notion of mobility diversity scheme through a simple example, and show that for this simple case, mobility of the nodes with respect to each other significantly improves the performance of the network.

II. Problem Setup and Data Model

Consider a wireless sensor network with several sensor nodes and a few sink nodes. Assuming single-hop communication scheme, each sensor node can transmit its data to the server (fusion center) only if it is within a distance d of at least one of the sinks. In case of a stationary network, the sensors and sink nodes are deployed properly so that each sensor node *sees* at least one sink. However, in a mobile wireless network, the nodes are mobile and thus the node-to-node distances are constantly changing. In such a scenario, the network performance highly depends on the topology of the network. The "best" topology is the one where every sensor node is in the access range d of at least one sink node. If a certain sensor node cannot see any of the sink nodes, the information sensed by that node cannot reach any of the sinks, and it will be lost or delayed. In this scenario, node mobility can significantly improve the communication performance as it continuously changes the topology and thus the node connectivity. A sensor node that is not close enough to any sink node in a certain time instance, could be in the proximity of a sink node in the next time instance due to its mobility or due to the sink nodes' mobility. In other words, the change in the network topology provides opportunities for new links between the nodes to be established.

If the nodes are moving independent of each other, observation time instances can be chosen such that the topologies of the networks in different time instances are *statistically independent*. This implies that, each node will have the opportunity to transmit its data over independent channels (topologies) and this is what we refer to as the mobility or topology diversity.

In order to analytically study the concept of mobility diversity, we consider a simple scenario, where a single sensor node and $\mathbf{m}_{\rm s}$ sink nodes are randomly moving along the x-axis. Each sink can collect the information of the sensor node only if the sensor lies within the distance d of that sink. Different nodes are assumed to be moving independently on the x-axis.

We model the nodes' locations on the x-axis as Brownian motion processes and assume that the coordinate of the sensor node and that of the jth sink are respectively denoted by random processes $\mathbf{x}(t)$ and $\mathbf{y}_j(t)$, for $t \geq 0$, and for $j = 1, 2, \ldots, \mathbf{m}_{\rm s}$. We model these random processes as

$$\mathbf{x}(t) = \sigma_0 \mathbf{v}_0(t) \quad (1)$$

$$\mathbf{y}_j(t) = \mathbf{y}_j(0) + \sigma_j \mathbf{v}_j(t), \;\; j = 1, 2, \ldots, \mathbf{m}_{\rm s} \quad (2)$$

where $\{\mathbf{y}_j(0)\}_{j=1}^{\mathbf{m}_{\rm s}}$ are the random positions of the sink nodes at $t = 0$, σ_0 and σ_j denote the so-called *mobility parameters* of the sensor node and the jth sink node, respectively, and the random processes $\{\mathbf{v}_j(t)\}_{j=0}^{\mathbf{m}_{\rm s}}$ are statistically independent standard Brownian motion processes, that is

$$\mathbf{v}_j(t) \sim \mathcal{N}(0, t), \; \mathbf{v}_j(0) = 0, \;\; j = 0, 1, \ldots, \mathbf{m}_{\rm s}$$
$$f_{\mathbf{v}_j, \mathbf{v}_l}(x, y; t_1, t_2) = f_{\mathbf{v}_j}(x; t_1) f_{\mathbf{v}_l}(y; t_2)\;, \text{ for } j \neq l$$

where $\mathcal{N}(a, b)$ refers to a normal distribution with mean a and variance b and $f_{\mathbf{v}_j}(x; t)$ is the probability density function of the jth process at time t. Based on (1), at $t = 0$, the sensor node is at the origin. The network topology then evolves and the location of the sensor node is observed at n time instances $\{t_k\}_{k=1}^{n}$.

It is worth mentioning here that although one dimensional mobility is not a realistic assumption, this assumption is a commonly used in assessing the effect of mobility on the performance of wireless networks (see [16] for instance). This is because the analysis based on one dimensional mobility can be extended to higher dimensions if some conditions, such as independence of the mobility on perpendicular directions, are satisfied. Furthermore, our analysis can be readily extended to the case of multiple sensors if the motion of sensor nodes are independent. Therefore, the one dimensional single sensor case, cab be used as a basis for more general mobility scenarios.

III. Analysis

In this section, we show that *the average number of time instances where the sensor node is in the d-proximity of at least one sink node is an increasing function of sensor mobility parameter* σ_0. To do so, let us define the indicator random variable

$$\mathbf{I}_k = \begin{cases} 1, & \text{sensor is in the } d\text{-proximity of a sink at } t = t_k \\ 0, & \text{sensor is } \textit{not} \text{ in the } d\text{-proximity of a sink at } t = t_k. \end{cases}$$

It is obvious that the cases where the random sequence $\{\mathbf{I}_k\}_{k=1}^{n}$ has more ones than zeros are favorable to the sensor node as this means that, the sensor is close to at least one sink node most of the time, and thus, it can communicate out its information. Based on this observation, we define the random variable $\mathbf{N}$ as the number of time instances where the sensor node is in the proximity of at least one sink node or simply as the number of ones in the binary random sequence $\{\mathbf{I}_k\}_{k=1}^{n}$, that is

$$\mathbf{N} = \sum_{k=1}^{n} \mathbf{I}_k\,. \quad (3)$$

Note that the random variable $\mathbf{N}$ is closely related to the the number of messages (packets) that the sensor node can transmit over a particular sequence of network topologies it observes at time instances $\{t_k\}_{k=1}^{n}$. Denoting the statistical expectation as $\mathbb{E}\{\cdot\}$, we now compute $\mathbb{E}\{\mathbf{N}\}$ based on the assumption that at $t = 0$, the sinks are uniformly distributed in the interval $[-D, \; -h] \cup [h, \; D]$ with density $\lambda_{\rm s}$, i.e., the number of sink nodes $\mathbf{m}_{\rm s}$ is a Poisson random variable with mean $2\lambda_{\mathrm{s}}(D-h)$. That is

$$f_{\mathbf{y}_j}(y;0)=\begin{cases}\dfrac{1}{2D-2h} & y\in[-D,\ -h]\bigcup[h,\ D]\\ 0 & \text{otherwise}\end{cases} \tag{4}$$

and

$$\Pr\{\mathbf{m}_{\mathrm{s}}=m\}=\frac{e^{-2\lambda_{\mathrm{s}}(D-h)}(2\lambda_{\mathrm{s}}(D-h))^m}{m!}. \tag{5}$$

Note that the sink node pdf in (4) implies that at $t=0$, the sensor node is not in the vicinity of any sink node. We choose $h>d$ to ensure that the sensor node is *not* initially connected. Based on the definition of $\mathbf{N}$, we have

$$\mathbb{E}\{\mathbf{N}\}=\mathbb{E}\left\{\sum_{k=1}^{n}\mathbf{I}_k\right\}=\sum_{k=1}^{n}\Pr\{\mathbf{I}_k=1\}. \tag{6}$$

We define the random processes $\mathbf{z}_j(t)=|\mathbf{x}(t)-\mathbf{y}_j(t)|$, for $j=1,2,\ldots,\mathbf{m}_{\mathrm{s}}$, to be the distance between the sensor node and the jth sink at time t. Being connected to a sink at time t is equivalent to $\min_j \mathbf{z}_j(t)<d$, which means that at least one sink node is in the d-proximity of the sensor. Using this observation, we rewrite $\Pr\{\mathbf{I}_k=1\}$ as

$$\begin{aligned}\Pr\{\mathbf{I}_k=1\} &= \Pr\{\min_j \mathbf{z}_j(t_k)\le d\}\\ &= 1-\Pr\{\min_j \mathbf{z}_j(t_k)>d\}\\ &= 1-\Pr\{\mathbf{z}_1(t_k)>d,\ldots \mathbf{z}_{\mathbf{m}_{\mathrm{s}}}(t_k)>d\}.\end{aligned}$$

While the random processes $\{\mathbf{z}_j(t)\}_{j=1}^{\mathbf{m}_{\mathrm{s}}}$ are not independent for different j, they are independent conditioned on the value of $\mathbf{x}(t)$. Indeed, if $\mathbf{x}(t)$ is known, $\{\mathbf{z}_j(t)\}_{j=1}^{\mathbf{m}_{\mathrm{s}}}$ are functions of $\{\mathbf{v}_j(t)\}_{j=1}^{\mathbf{m}_{\mathrm{s}}}$, which are assumed to be independent. Therefore,

$$\begin{aligned}&\Pr\{\mathbf{I}_k=1\}\\ &=1-\int_{\mathbb{R}}\left\{\prod_{j=1}^{\mathbf{m}_{\mathrm{s}}}\Pr\left\{\mathbf{z}_j(t_k)>d\,\Big|\,\mathbf{x}(t_k)=x\right\}\right\}f_{\mathbf{x}}(x;t_k)dx\\ &=1-\int_{\mathbb{R}}\left(\prod_{j=1}^{\mathbf{m}_{\mathrm{s}}}1-\Pr\{x-d<\mathbf{y}_j(t_k)<x+d\}\right)f_{\mathbf{x}}(x;t_k)dx\\ &=1-\int_{\mathbb{R}}\left(\prod_{j=1}^{\mathbf{m}_{\mathrm{s}}}\int_{\bar{I}_d(x)}f_{\mathbf{y}_j}(y;t_k)dy\right)\ f_{\mathbf{x}}(x;t_k)dx\end{aligned} \tag{7}$$

where $\bar{I}_d(x)=\mathbb{R}-(x-d,x+d)$ and

$$f_{\mathbf{x}}(x;t_k)=\frac{1}{\sigma_0\sqrt{2\pi t_k}}e^{-\dfrac{x^2}{2\sigma_0^2 t_k}}. \tag{8}$$

As the sink nodes are assumed to be distributed uniformly in the interval $[-D,D]$, the number of sink nodes $\mathbf{m}_{\mathrm{s}}$ is a Poisson random variable, and hence, (7) can be written as

$$\begin{aligned}&\Pr\{\mathbf{I}_k=1\}=1-\\ &\sum_{m=0}^{\infty}\int_{\mathbb{R}}\left(\prod_{j=1}^{m}\int_{\bar{I}_d(x)}f_{\mathbf{y}_j}(y;t_k)dy\right)\Pr\{\mathbf{m}_{\mathrm{s}}=m\}f_{\mathbf{x}}(x;t_k)dx.\end{aligned} \tag{9}$$

Denoting the term under the product as $g_j(x,t_k)$, we have

$$\begin{aligned}&g_j(x,t_k)=1-\Pr\{x-d<\mathbf{y}_j(t_k)<x+d\}=\\ &1-\int_y \Pr\left\{x-d<\mathbf{y}_j(t_k)<x+d\,\Big|\,\mathbf{y}_j(0)=y\right\}f_{\mathbf{y}_j}(y;0)dy\\ &=1-\int_{-D}^{D}\int_{x-d}^{x+d}f_{\mathbf{y}_j(t_k)|\mathbf{y}_j(0)}(y'|y)f_{\mathbf{y}_j}(y;0)dy'dy+\\ &\int_{-h}^{h}\int_{x-d}^{x+d}f_{\mathbf{y}_j(t_k)|\mathbf{y}_j(0)}(y'|y)f_{\mathbf{y}_j}(y;0)d\tau dy.\end{aligned} \tag{10}$$

The Markovian property of the Brownian motion process implies that

$$f_{\mathbf{y}_j(t_k)|\mathbf{y}_j(0)}(y'|y)=\frac{1}{\sigma_j\sqrt{2\pi t_k}}\exp\left(-\frac{(y'-y)^2}{2\sigma_j^2 t_k}\right).$$

Also $f_{\mathbf{y}_j}(y;0)$ is given as in (4). Therefore,

$$\begin{aligned}g_j(x,t_k)&=1-\frac{1}{2(D-h)\sigma_j\sqrt{2\pi t_k}}\times\\ &\left\{\int_{-D}^{D}\int_{x-d}^{x+d}\exp\{-\frac{(y'-y)^2}{2\sigma_j^2 t_k}\}d\tau dy\right.\\ &\left.-\int_{-h}^{h}\int_{x-d}^{x+d}\exp\{-\frac{(\tau-y)^2}{2\sigma_j^2 t_k}\}d\tau dy\right\}.\end{aligned} \tag{11}$$

Using (9) and (11) in (3), we obtain that

$$\begin{aligned}&\mathbb{E}\{\mathbf{N}\}=\\ &n-\sum_{k=1}^{n}\sum_{m=0}^{\infty}\int_{\mathbb{R}}\left(\prod_{j=1}^{m}g_j(x,t_k)\right)\Pr\{\mathbf{m}_{\mathrm{s}}=m\}f_{\mathbf{x}}(x;t_k)dx.\end{aligned} \tag{12}$$

If we assume that the mobility parameters of all sink nodes are equal, i.e., $\sigma_j=\sigma\neq\sigma_0$, for $j=1,2,\ldots,\mathbf{m}_{\mathrm{s}}$, then $g_j(x,t_k)$ is the same for all values of j, and hence, we can further simplify (12). In this case, we can write

$$\begin{aligned}&\Pr\{\mathbf{I}_k=1\}\\ &=1-\sum_{m=0}^{\infty}\int_{\mathbb{R}}g(x,t_k)^m\Pr\{\mathbf{m}_{\mathrm{s}}=m\}f_{\mathbf{x}}(x;t_k)dx\\ &=1-\int_{\mathbb{R}}f_{\mathbf{x}}(x;t_k)e^{-2\lambda_{\mathrm{s}}(D-h)}\sum_{m=0}^{\infty}\frac{(2g(x,t_k)\lambda_{\mathrm{s}}(D-h))^m}{m!}dx\\ &=1-\int_{\mathbb{R}}f_{\mathbf{x}}(x;t_k)e^{-2\lambda_{\mathrm{s}}(D-h)(1-g(x,t_k))}dx\end{aligned} \tag{13}$$

Hence, for this special case, (12) will be written as

$$\mathbb{E}\{\mathbf{N}\} = n - \sum_{k=1}^{n} \int_{\mathbb{R}} f_{\mathbf{x}}(x;t_k) e^{-2\lambda_{\text{s}}(D-h)(1-g(x,t_k))} dx . \quad (14)$$

In the next section, we will discuss these results in further details.

IV. Discussion

For very large values of σ_0, the distribution of the position of the sensor node at time t_k ($f_{\mathbf{x}}(x;t_k)$) becomes almost flat within the range $[-D, D]$, meaning that the sensor node can randomly be anywhere in this interval at each observation time. It is readily seen that in this case, $\mathbb{E}\{\mathbf{N}\}$ depends only on the distribution of the sink nodes and their mobility parameters through the function $g(x,t_k)$. In the special case that the sink nodes are stationary, $\Pr\{\mathbf{I}_k = 1\} = \lambda_{\text{s}}$ and therefore, $\mathbb{E}\{\mathbf{N}\} = n\lambda_{\text{s}}$. To investigate the effect of the sensor mobility parameter σ_0 on the integral in (13), we first study the function $g(x,t_k)$. The derivative of $g(x,t_k)$ w.r.t. x (11) is easily shown to be

$$\frac{\partial g(x,t_k)}{\partial x} = \left\{ \int_{y=-h}^{h} \exp\{-\frac{(y-(x+d))^2}{2\sigma_j^2 t_k}\} dy - \int_{y=-h}^{h} \exp\{-\frac{(y-(x-d))^2}{2\sigma_j^2 t_k}\} dy \right\} - \left\{ \int_{y=-D}^{D} \exp\{-\frac{(y-(x+d))^2}{2\sigma_j^2 t_k}\} dy - \int_{y=-D}^{D} \exp\{-\frac{(y-(x-d))^2}{2\sigma_j^2 t_k}\} dy \right\}. \quad (15)$$

It can be easily seen that for $x = 0$, $\frac{\partial g(x,t_k)}{\partial x} = 0$. It can also be readily proven that

$$\frac{\partial g(x,t_k)}{\partial x} < 0, \text{ for } x > 0 \quad \text{and} \quad \frac{\partial g(x,t_k)}{\partial x} > 0, \text{ for } x < 0.$$

This means that the function $g(x,t_k)$ has a single maximum at $x = 0$. As $g(x,t_k)$ represents the probability of an event, and hence, it is limited between 0 and 1, $1 - g(x,t_k)$ has a minimum at $x = 0$, and consequently, $h(x) \triangleq \exp(-2\lambda_{\text{s}}(D-h)(1-g(x,t_k)))$ has a maximum at $x = 0$ with positive derivative for negative x and negative derivative for positive x. In other words, $xh'(x) < 0$ for all x where $h'(x)$ represents the derivative of $h(x)$ with respect to x. Using these properties of the functions $g(x,t_k)$ and $h(x)$, we will now prove that $\Pr\{\mathbf{I}_k = 1\}$, and hence, $\mathbb{E}\{\mathbf{N}\}$ are both increasing functions of the sensor mobility parameter σ_0. To show this, we differentiate (13) with respect to σ_0 and write

$$\begin{aligned} \frac{\partial}{\partial \sigma_0} \Pr\{\mathbf{I}_k = 1\} &= \frac{\partial}{\partial \sigma_0} \left(1 - \int_{\mathbb{R}} f_{\mathbf{x}}(x;t_k) h(x) dx \right) \\ &= \frac{1}{\sigma_0} \Pr\{\mathbf{I}_k = 1\} - \int_{\mathbb{R}} \frac{x^2}{\sigma_0^4 \sqrt{2\pi t_k}} e^{-\frac{x^2}{2\sigma_0^2 t_k}} h(x) dx \\ &= -\frac{1}{\sigma_0^2 \sqrt{2\pi t_k}} \int_{\mathbb{R}} x h'(x) e^{-\frac{x^2}{2\sigma_0^2 t_k}} dx. \end{aligned} \quad (16)$$

As we earlier proved that for all values of x, $xh'(x)$ is negative, the last integral in (16) is always negative which implies that $\frac{\partial}{\partial \sigma_0} \Pr\{\mathbf{I}_k = 1\} > 0$. In other words, the increase in sensor mobility increases the probability of a sensor node being in the d-proximity of a sink node and consequently increases the *average number of time instances* ($\mathbb{E}\{\mathbf{N}\}$) *at which the sensor can communicate to a sink node*.

V. Numerical Evaluation

Fig. 1 shows the average number of time instances, for which the sensor is in d-proximity of at least one sink node, versus the initial density of the sink nodes λ_{s}, for different values of the sensor mobility parameter σ_0. Fig. 2 illustrates the average number of time instances, for which the sensor is in d-proximity of at least one sink node, versus the sensor mobility parameter σ_0, for different values of the initial density of the sink nodes λ_{s}. These figures have been produced for a system with sink nodes randomly uniformly distributed in a range of 1000 meters ($D = 500$ m) except for a range of length 40 meters centered at the origin (where the sensor node is initially located) corresponding to $h = 20$ m. Each sink node can collect the sensor node's information if their distance does not exceed 20 meters ($d = 20$ m). The sink nodes are all moving with the same mobility parameter $\sigma_j = \sigma$; for $j = 1, 2, \ldots, \mathbf{m}_{\text{s}}$. The curves illustrated in these figures are the numerical evaluations of $\mathbb{E}\{\mathbf{N}\}$ using (14). We have also used Monte Carlo simulations to calculate $\mathbb{E}\{\mathbf{N}\}$. The corresponding curves precisely coincide with the theoretical ones plotted in Figs. 1 and 2, and therefore, they have not been plotted in these figures.

We observe the network connectivity at $t = 5, 7, 9, \ldots,$ 23 seconds, and hence, the $\mathbf{N} \leq 10$. As can be seen from these figures, the expected number of instances, where the sensor node can successfully transmit its data increases with the initial density of the sink nodes and also with the mobility parameter of the sensor node. The diversity introduced by the mobility is evident in these figures. The more *mobile* the network becomes, the larger will be the chance of connectivity in different time instances and collectively, having a larger average number of successful transmissions.

It is also worth mentioning that we can extend our analysis to the case of multiple sensor nodes if the motion of the sensor nodes are assumed independent. In such a case, if there are S sensor nodes, at any time instance, the probability of all sensors being connected to at least one of the sinks is the product of the connectivity probabilities for each of them, and the latter has already been calculated in this paper.

VI. Conclusion

In this paper, we introduced the novel concept of *mobility diversity* for mobile sensor or communication networks as the diversity introduced by transmitting data over different topologies of the network. We showed how node mobility can provide diversity by changing the topology of the network and studied a simple network with one dimensional mobility. More specifically, we considered a mobile network with a sensor

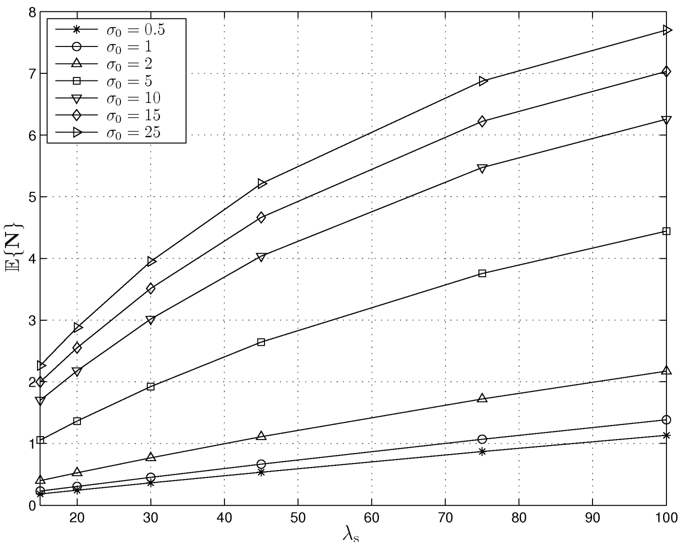

Fig. 1. The average number of time instances, for which the sensor is in d-proximity of at least one sink node, versus the initial density of the sink nodes λ_s, for different values of the sensor mobility parameter σ_0.

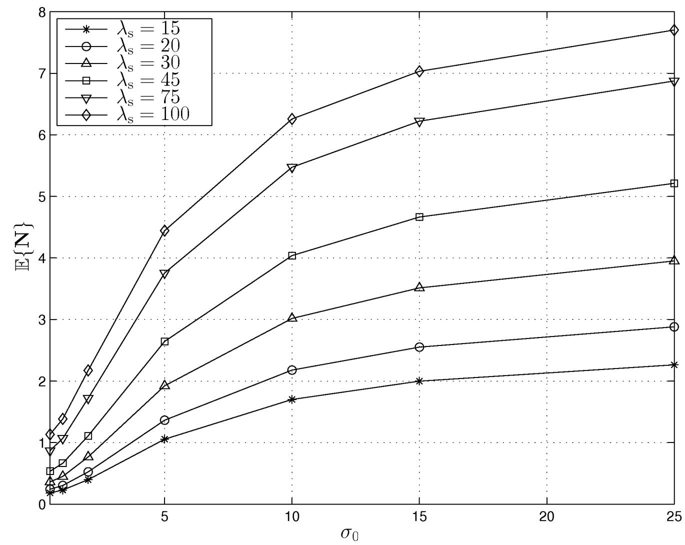

Fig. 2. The average number of time instances, for which the sensor is in d-proximity of at least one sink node, versus the sensor mobility parameter σ_0, for different values of the initial density of the sink nodes λ_s.

node and a number of sink nodes moving along the x-axis and used a Brownian motion model to describe a one-dimensional mobility. Assuming that the network topology evolves with time and assuming that the connectivity of the sensor node to at least one sink, is needed for the successful data collection, we calculated the expected number of time instances, where the sensor node is connected to at least one sink, and hence, it can transmit its data. Our theoretical analysis and numerical experiment show that increasing the mobility parameter of the sensor node results in larger chance of connectivity confirming the gain achieved by the mobility diversity.

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