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# Topology Sensing of Wireless Networks Based on Hawkes Process

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**Abstract**
With the popularization of wireless heterogeneous networks, it is becoming more and more important to infer network behavior. Topology sensing, as a fundamental issue in the field of network confrontation, can help network make optimal decisions. However, most of the related studies focus on topology sensing with complete and perfect observations, while the characteristics of wireless channel are relatively few investigated. Consequently, this paper investigates the issue of wireless network topology sensing with unreliable information caused by imperfect channels. First, a robust system model for external topology sensing considering unreliable information is formulated. Then, a wireless channel-oriented topology sensing scheme based on Hawkes process is proposed to address the challenge of unreliable information. In addition, simulations are carried out to demonstrate that the scheme we proposed is effective to deal with the imperfect channels. The performance under various parameter configurations is also analyzed, which can help us to find an optimal solution in practice.

**Keywords** Network confrontation · Wireless network · Topology sensing · Unreliable information · Hawkes process

## 1 Introduction

### 1.1 Background and motivation

With the popularization of wireless heterogeneous networks, it is becoming more and more important to infer network behavior [2, 3]. It was Bass that first proposed the term cyberspace situation awareness (CSA) and predicted that situation awareness technology based on data fusion would definitely become the development trend of network management analysis [4, 5]. Topology sensing, as one of the most critical technology of CSA, is used to infer the network connectivity according to the communication information. Wireless network topology sensing technology is indispensable to the management of its own communication network and the detection of the other network information. Through the interaction of topology information in its own network, the cooperative executive efficiency of network can be improved to help manager make optimal decisions. In addition, the sensing technology for detecting the other network topology is widely used. Through the information collection during a period of time, the connected relationship of the target communication network can be reasonably inferred, which is of great help for us to grasp the network situation.

Researches on intelligent analysis of network behavior, dynamic analysis of network topology and real-time analysis of key nodes/links can realize automatic identification of network nodes, dynamic analysis of network connectivity and automatic generation of network topology. Network topology sensing is a new paradigm based on cognitive radio, but the shortage of spectrum resources has limited the development of network intelligence [6, 7]. Actually, traditional network topology sensing usually requires a lot of prior information, such as operating modes and network protocols. These observations motivate us in this paper to investigate the issue of topology sensing of wireless networks with unreliable information.

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### 1.2 Related work

Early topology sensing works mainly used the method of graph [8]. Relevant tools for graph connectivity inference include vector autoregression model (VARMs) [9], structural equation model (SEMs) [10], dynamic causality model (DCMs) [11, 12] and granger causality (GC) [13, 14]. All of them are based on causality to infer the network topology. The authors in [9] proposed to use a multivariate statistical method—Multivariate Vector Autoregression (MVAR) to infer dynamic microbial interactions from the time series of human gut microbiomes. SEM is widely used in sociometrics [15], psychometrics [16], genetics [17] and dynamic evolutionary social networks [18–20]. It is a multivariate statistical technique, which combines factor analysis and path analysis. Its strength lies in the quantitative study of the interaction between variables. The authors in [11] proposed a process interpretation of causality and the first-order causal process (FOCP) model for temporal causal modelling. Experiments on both simulated and real data validate the feasibility of the method to discover simple while meaningful causal structures of dynamic systems.

The other two methods are Hawkes process [21] and transfer entropy [22]. Information interaction processes were modeled as Hawkes process to infer network connectivity in [23]. The authors in [22] proposed a method based on transfer entropy to quantify the correlation of network nodes. With the development of Ad-hoc network, more and more scholars begin to pay attention to the problem of topology sensing. The authors in [24] inferred the physical topology of Ad Hoc network with critical transmission distance under the condition that the location information and the number of nodes, the size of the deployment area are known. Then a graph topology inference based on transform learning was proposed by the authors in [25, 26] from signals defined over the vertices of a graph.

However, the above works have their limitations: First, a clear system model considering unreliable information has not been formulated. Second, the application conditions are so harsh that they are unable to adapt to complex real scenarios. Thus, in this paper, we investigate the issue of topology sensing of wireless networks in communication processes with imperfect channels.

### 1.3 Contributions

The main contributions of this paper are summarized as follows:

– We formulate a robust system model for external topology sensing considering unreliable information caused by imperfect wireless channels.
– We propose a robust wireless channel-oriented topology sensing scheme based on Hawkes process to deal with the unreliable information and the interference with multi-hop connectivity.
– We present in-depth simulations under various parameter configurations, which can help us to find an optimal solution in practice.

The rest of this paper is organized as follows. Section 2 introduces the system model and problem formulation. In Section 3, a robust wireless channel-oriented topology sensing scheme based on Hawkes process is proposed. Then, in Section 4, we give the simulation results under various parameter configurations. In addition, the conclusions and future works are mentioned in Section 5.

## 2 System model and problem formulation

### 2.1 Topology sensing model

In this paper, we consider a topology sensing model as shown in Fig. 1, in which $V$ is an unknown wireless network and $S$ is a sensor. As an external observer of the network, how to infer the network topology through effective algorithm under the condition of unreliable information, is the problem to be solved.

For the target network $V$, there are $N$ terminal nodes working together and they communicate with each other by wireless connection. Because of the communication setup, they can only transmit data to specific nodes. In this paper, we do not consider the directivity of wireless communication links and all links must be used for several times in a sensing period.

The sensor outside of the target network plays an important role in this sensing system, the decision of which directly determines the accuracy of topology inference. We assume that the location and number of network nodes are known by sensors, the basis functions of which are signal detection [27] and target recognition [28, 29]. There are only two kinds of information available to external observer: the node that transmits the data and the time when the transmission takes place.

The process can be described as follows. The sensor $S$ monitors the transmission of information in the network $V$ from $t = 0$ to $t = T$. Once the information transmission happens, the corresponding event and time are automatically recorded. In the end, we can get two one-to-one corresponding sequences. The sequence of the originator is called the set of events, and the sequence of the recording time is called the set of times. Through the corresponding calculation of these initial data, the interconnection of the network nodes will be gotten.

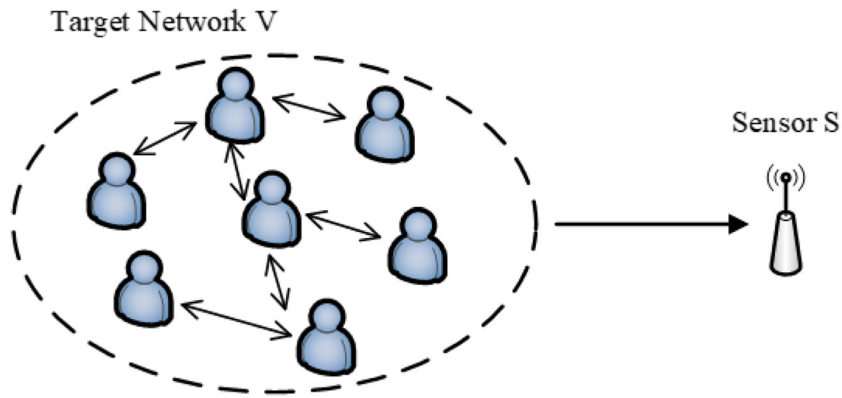



**Fig. 1** The system model of topology sensing

**Algorithm 1** Topology sensing algorithm based on Hawkes process with single sensor.

**Input:** The number of nodes in the network, $N$; The set of events, $\mathbf{E_n}$; The set of times, $\mathbf{E_t}$; The influence matrix threshold, $\alpha$;
**Output:** Recovered influence matrix, $\mathbf{A}$;
1: Initialize $\mu$, $\mathbf{A}$
2: Sort $\mathbf{E_n}$ and $\mathbf{E_t}$;
3: **for** each $i \in [1, N]$ **do**
4: $\lambda_i(t) = \mu_i + \sum_{j=1}^{N} A_{ij} \sum_{k \in K_j} \gamma\,(t - t_k)$
5: $[\mu, \mathbf{A}] = \underset{\mu,\mathbf{A}}{\operatorname{argmin}} L(\mu, A)$
6: **end for**
7: Remove all $A_{ij}$ which less than $\alpha$;
8: Symmetrization $\mathbf{A}$.

### 2.2 Wireless channel model

There are two wireless channels in this problem, as shown in Fig. 1: One is the communication links among nodes in the target network, and the other is the sensing channels between nodes and sensor, through which information is monitored by sensor outside of the network. For the communication links, because the target network we want to know is mostly used in special occasions, we have reason to believe their high reliability. Therefore, in order to simplify the problem, we do not consider the randomness of this channel. For the sensing channels, since the sensor listens in private without the permission of the network, it is likely to be subject to various external interference, so the randomness of this channel cannot be ignored.

After considering the wireless channels, the problem of signal detection is necessary. The signal detection of topology sensing is essentially a binary hypothesis-testing problem [30]

$H_0$ : Signal is absent
$H_1$ : Signal is present.

The correct detection probability given by $P_d = P_r(H_1|H_1)$ and the false alarm probability given by $P_f = P_r(H_1|H_0)$ are the key metrics. The signal detection problem is to decide between the following two hypotheses [31]:

$$y(t) = \begin{cases} \varepsilon(t), t \in [0, T] & H_0 \\ \sqrt{P_r^{(i)}} x^{(i)}(t) + \varepsilon(t), t \in [0, T] & H_1 \end{cases} \tag{1}$$

in which $T$ is the topology sensing period, $x^{(i)}(t)$ is the signal from the $i$th node in the time $t$, $y(t)$ is the signal detected by the sensor, $\varepsilon(t)$ is the additive white gaussian noise of the sensor and $P_r^{(i)}$ is the signal power that received by the sensor from the $i$th node. Therefore, the binary hypothesis-testing problem can be described as follows:

$$\begin{aligned} H_0 &: E(t) < \lambda \\ H_1 &: E(t) > \lambda, \end{aligned} \tag{2}$$

where $E(t)$ is the signal energy that received by the sensor and $\lambda$ is the signal detection threshold.

### 2.3 Problem formulation

In this section, we prefer using Hawkes process to model the communication. Hawkes process is an autoregressive point process, whose main idea is that the occurrence probability of an event at any time is a function of the recent events in the process.

For an event, in a case which has given $t_k$, the occurrence probability of the event is

$$\lambda(t) = \mu(t) + A \sum_{k=1}^{K} \gamma\,(t - t_k)\,, \tag{3}$$

which can also be called conditional intensity function (CIf). The parameter $\mu(t) \geq 0$ is the basic rate of the event or the rate of innovation; the parameter $A \geq 0$ indicates the degree of self-motivation of the event, that is, how much influence the event at time has on the occurrence of the event at time, so we can call it the self-motivation matrix; the kernel function $\gamma(t)$ represents the time relationship between the events, which is known, causal, non-negative and integrable. Here we take it as $\gamma(t) = e^{-t}$.

This model can be easily extended to the process containing multiple subprocesses, where the occurrence probability of one subprocess is affected not only by its own behavior, but also by the behavior of other subprocesses. We can use the multi-dimensional Hawkes process to model the communication processes in wireless networks, and regard every information transmission in the network as a subprocess. For the process with $N$ subprocesses, the CIf of the $i$th subprocess can be obtained as

$$\lambda_i(t) = \mu_i + \sum_{j=1}^{N} A_{ij} \sum_{k \in K_j} \gamma\left(t - t_k\right), \tag{4}$$

in which $K_j$ represents the event set in the $j$th subprocess, $\mu_i$ represents the basic rate of the $i$th subprocess, which we think is constant, $A_{ij}$ quantifies how much the $i$th subprocess reacts to $j$th subprocess, and $A_{ij} = 0$ represents the occurrence of the $j$th subprocess has no effect on the $i$th subprocess, and $A_{ij} > 0$ represents that the occurrence of the $j$th subprocess will lead to the temporary increase of the occurrence probability of the $i$th subprocess.

## 3 Topology sensing scheme in wireless channels

### 3.1 Determination of Hawkes process parameters

In many cases, parameters cannot be known beforehand, so we need to use mathematical tools to reasonably infer the parameters according to the observed values in a certain period of time [32, 33]. Here we use the maximum likelihood estimation method to determine $\mu$ and $A$. The negative log-likelihood function of the $i$th subprocess is

$$L_i(\mu, A) = \int_0^T \lambda_i(t) - \sum_{k \in K_i} \log \lambda_i\left(t_k\right). \tag{5}$$

Maximum likelihood function requires us to minimize this convex function and there are many ways to choose. Because $\lambda_i(t)$ only depends on the $\mu$ and $A$ in a line, we can independently optimize the likelihood in the process of each subproblem. Through practice, we find that the quasi-Newton method is simple and effective, so we finally use quasi-Newton method in the program.

### 3.2 Threshold and symmetry

Using the influence matrix obtained by Hawkes process and maximum log-likelihood function, redundant links can easily be generated due to a little interference. Besides, the Hawkes process cannot remove the interference of multi-hop connectivity. For example, if the node $i$ can transmit data to the node $j$ through the node $k$, the transmitting possibility of the node $j$ will improved when the node $i$ transmit data, but the node $i$ is not connected with the node $j$ directly. In order to deal with the above situations, we can set a threshold to reduce redundant links, which can achieve self-adaptation by analyzing the preliminary simulation results. However, we must admit that finding real links and reducing redundant links are contradictory. We need to balance the correct detection probability and false alarm probability according to different application scenarios and requirements.

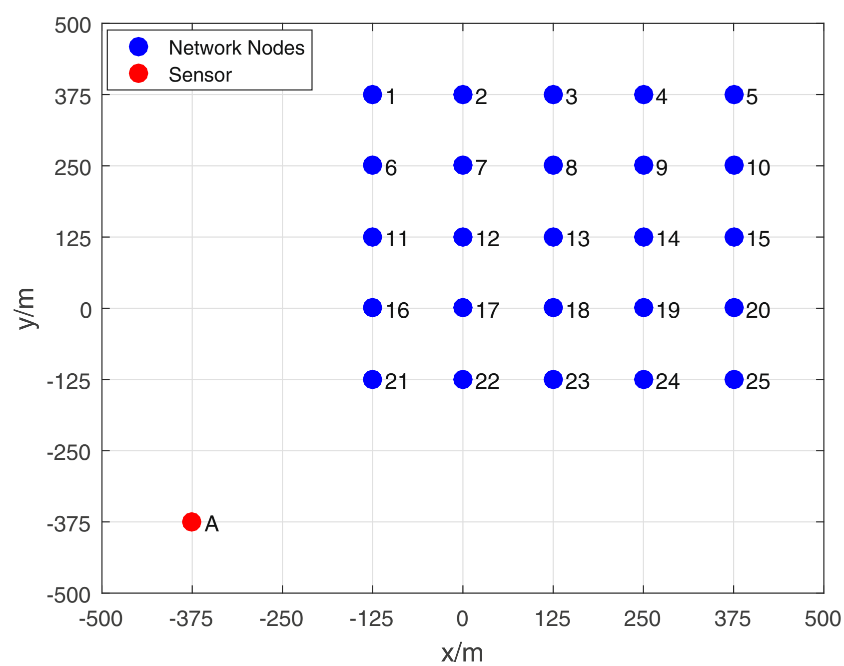



**Fig. 2** The location of the network nodes and sensor

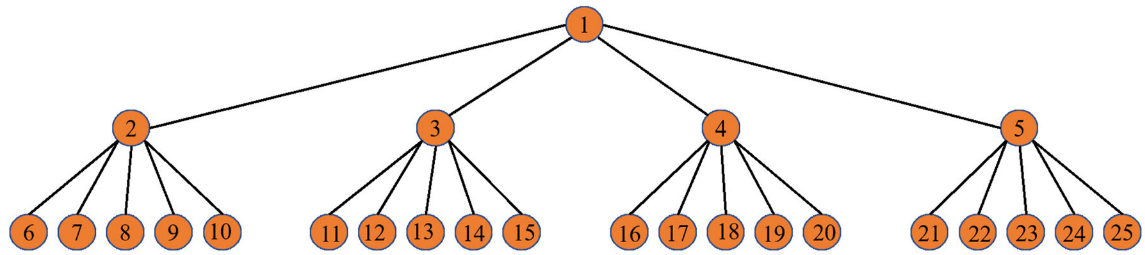



**Fig. 3** The tree topology

Because of the consideration of undirect links in the network, the influence matrix should be symmetrical, using which we can simply optimize the results. When $A_{ij} > 0$ and $A_{ji} > 0$, we think there is a connection, which we call the AND rule; when $A_{ij} > 0$ or $A_{ji} > 0$, we think there is a connection, which we call the OR rule. Selecting the AND rule will cause some real links not to be found, while the OR rule will cause link redundancy.

### 3.3 The topology sensing scheme

In conclusion, the topology sensing scheme based on Hawkes process is shown in Algorithm 1. The inputs are the number of nodes in the network, the set of events, the set of times and the influence matrix threshold. The output is the recovered influence matrix. The main idea of the scheme is to calculate the influence matrix using maximum likelihood function and then screen it by threshold and symmetry.

## 4 Simulations and discussion

### 4.1 Simulation initialization

In this section, we provide in-depth simulations of topology sensing in wireless networks with single sensor. Consider the scenario that shown in Fig. 2, in which there is a 25-node network and a sensor in a 1 km $\times$ 1 km area. The tree topology and the distributed topology will be simulated and they are shown in Figs. 3 and 4, respectively. Other simulation parameters are set as Table 1 shown.

We use receiver operating characteristic (ROC) curve [34] to compare performance of different parameters. $P_D = \frac{TP}{E}$ quantifies the true positive rate, $P_M = 1 - P_D$ is the false negative rate and $P_F = \frac{FP}{N(N-1)-E}$ quantifies the false positive rate, where $TP$ is the number of true positives, $FP$ is the number of the false positives and $E$ is the number of true links.

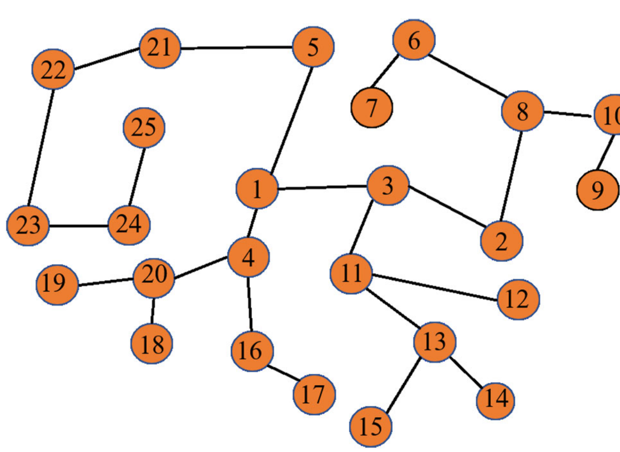



**Fig. 4** The distributed topology

### 4.2 Results with simulation data

#### 4.2.1 Impact of transmit power $P_s$

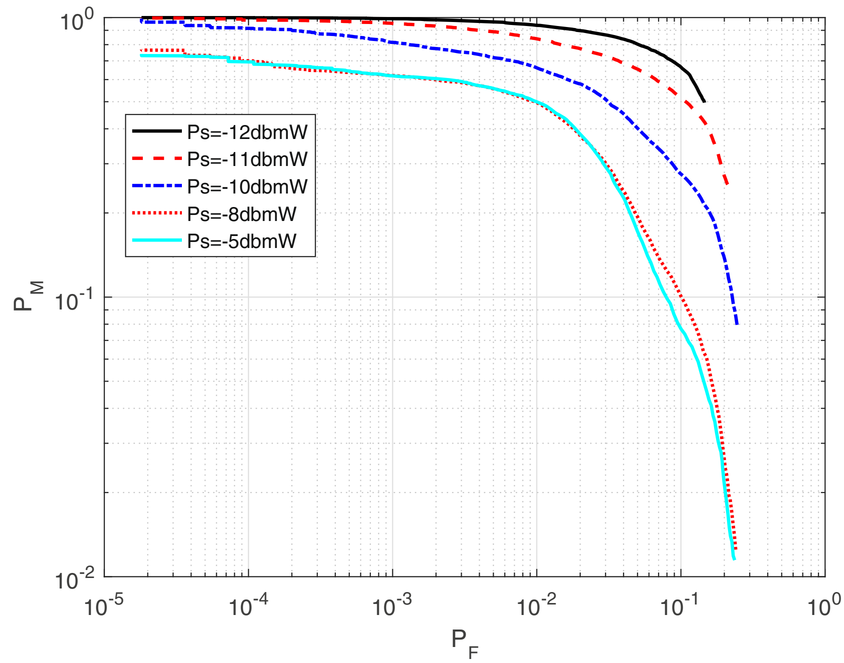
Considering that the receiver noise power is constant, because of the different distance between the network nodes and the sensor, the signal-to-noise ratios (SNR) are different in a sensing period. This motivates us to explore the impact of different transmit power on the results instead of SNR.

The performance under different transmit power $P_s$ with tree topology is shown in Fig. 5, in which the event number $N_{event} = 10$ and the signal threshold $\lambda = 5 \times 10^{-14}$ W. These results suggest that the transmit power has a great influence on sensing accuracy. The transmit power is higher, the performance is better. However, when the transmit

**Table 1** Simulation parameters

| Parameter | Value |
|---|---|
| Number of nodes in networks | 25 |
| Communication protocol | ARQ |
| Event number | $10 \sim 50$ |
| Sensing channel | AWGN |
| The receiver noise spectral density $n_0$ | $-174$ dBm/Hz |
| The noise bandwidth $W$ | 10 MHz |
| The signal transmit power $P_s$ | $-12$ dBmW $\sim -5$ dBmW |
| Signal detection threshold $\lambda$ | $3 \times 10^{-14}$ W $\sim 6 \times 10^{-14}$ W |

**Fig. 5** The ROC curve with different transmit power $P_s$




power is high enough, the sensing accuracy is not improved. It is because the pass loss will be offset by enough transmit power. Calculating the optimal transmit power can help us to infer the optimal distance between the network nodes and the sensor.

#### 4.2.2 Impact of event number $N_{event}$

Event number, the repetition times of every event, is also one of the most important parameters of topology sensing. Hawkes process is a probabilistic statistical method, so the links must be used for many times in the sensing period. The performance under different event numbers $N_{event}$ with tree topology is shown in Fig. 6, in which the transmit power $P_s = -10\text{dBmW}$ and the signal threshold $\lambda = 5 \times 10^{-14}$ W. As we expect, the event number is more, the sensing performance is better. Unlike transmit power, there is not a ceiling in event number. However, it does not mean that we should set a large event number, which will result in more time complexity and space complexity. Therefore,

**Fig. 6** The ROC curve with different event number $N_{event}$

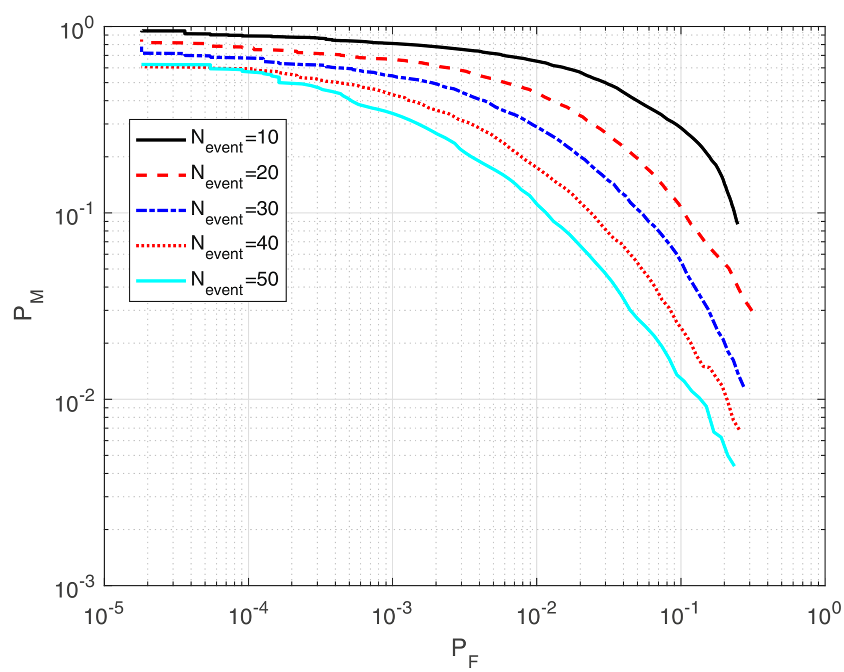
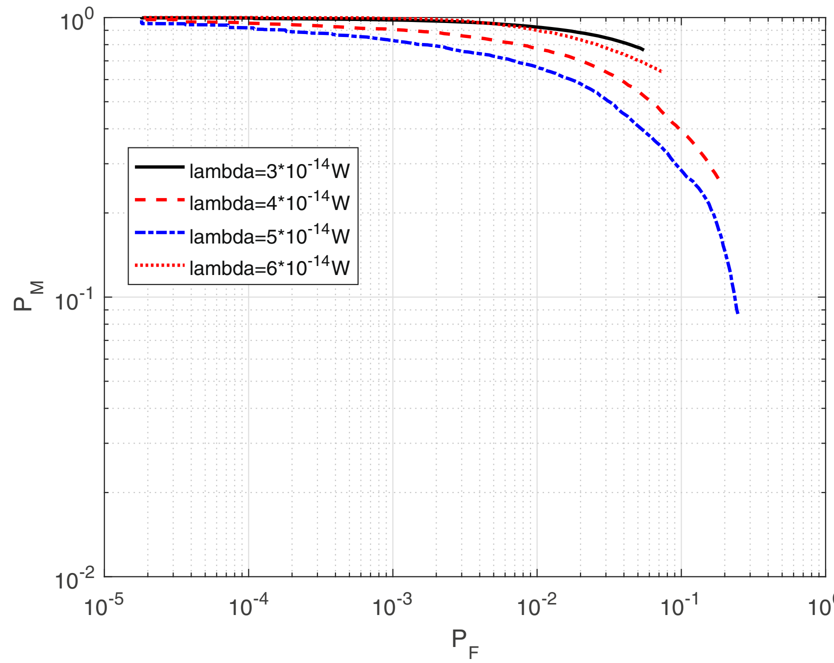


**Fig. 7** The ROC curve with different signal detection threshold $\lambda$

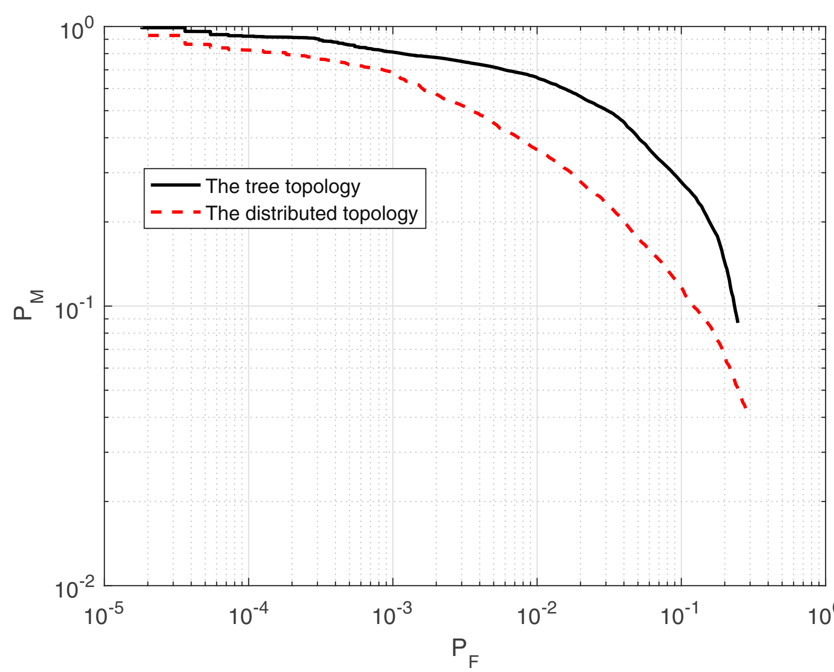



the set of event number must be the result of the balance between accuracy and complexity.

### 4.2.3 Impact of signal detection threshold λ

Signal detection accuracy results in the topology sensing performance so that the signal detection threshold is crucial. The performance under different signal detection thresholds $\lambda$ is shown in Fig. 7, in which the transmit power $P_s$ = −10 dBmW and the event number $N_{event} = 10$. It is found that the performance under $\lambda = 5 \times 10^{-14}$ W is better than the cases of $\lambda = 3 \times 10^{-14}$ W, $4 \times 10^{-14}$ W, $6 \times 10^{-14}$ W. It can be explained by correct detection probability $P_d$ and false alarm probability $P_f$. When the threshold is high, more signals are missed, even if the signal is present. When the threshold is low, more signals are selected by mistake, even if the signal is absent. The above two situations are both harmful to topology sensing.

**Fig. 8** The ROC curve with different topology



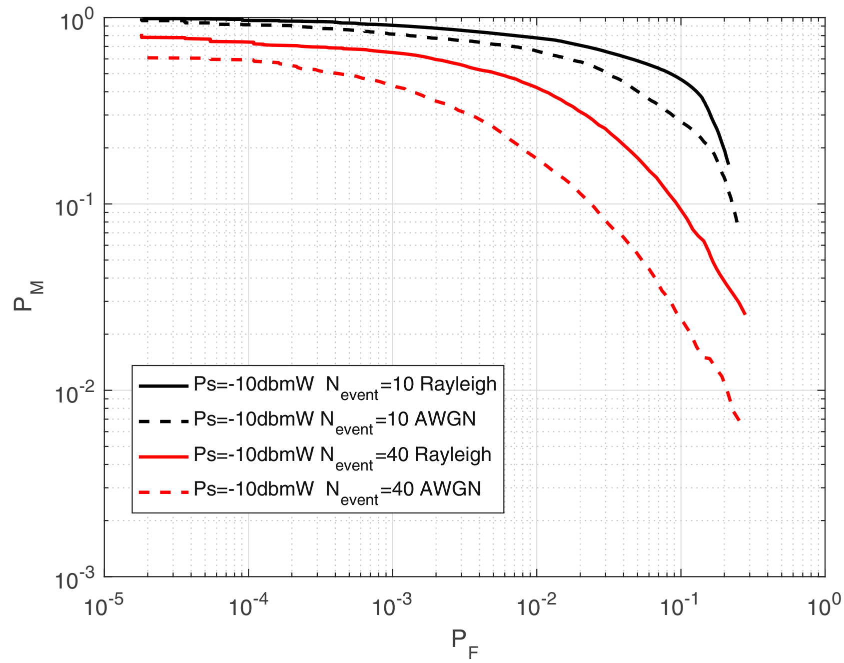



**Fig. 9** The comparisons between the performance in the Rayleigh channel and that in the AWGN channel

#### 4.2.4 Impact of topology

In this section, we analyze the impact of different topologies and the performance is shown in Fig. 8, in which the transmit power $P_s = -10$ dBmW, the event number $N_{event} = 10$ and the signal threshold $\lambda = 5 \times 10^{-14}$ W. The result suggests that the performance in a distributed topology is better than that in a tree topology. We can regard the tree topology as a kind of central topology. Compared with the distributed topology, the communication links are not used equally in the network with a central topology. The central node transmits more information than any other nodes. This situation results that some links are difficult to be identified correctly. However, in the network with a distributed topology, the communication links are used equally so that the topology sensing cannot interfere with each other.

#### 4.2.5 Performance in the Rayleigh channel

In order to further demonstrate the effectiveness of the algorithm in dealing with the channel randomness, we make some simulations in the Rayleigh channel in this section. The comparisons between the performance in the Rayleigh channel and that in the AWGN channel are shown in the Fig. 9. We determine the transmit Power $P_s = -10$ dBmW and compare the performance with the event number $N_{event} = 10$ and $N_{event} = 40$, respectively. In the Fig. 9, it is obvious that when $N_{event} = 10$, the performance in the Rayleigh channel closer to that in the AWGN channel. It shows that when channel fading is deep, the impact of event number on performance becomes insensitive. Because of the channel fading, it is acceptable that the performance in the Rayleigh channel is worse little than that in the AWGN channel. Therefore, to some extent, the algorithm is effective in the Rayleigh channel.

### 4.3 Results with real data

Considering the complexity of real communication environment, we also provide the simulations with real data. Table 2 is part of the original data, from left to right are the Index, Source ID, Destination ID, Start Time, Receive

**Table 2** The partial real data

| Idx | SrcID | DstID | StartTime (s) | ReceiveTime (s) | DstxPos | DstyPos |
|---|---|---|---|---|---|---|
| 1 | 93 | 24 | 17.234305 | 17.234356 | 0.067886 | −0.04369 |
| 2 | 24 | 93 | 17.23461 | 17.234668 | 0.05631 | −0.04242 |
| 3 | 93 | 24 | 17.234822 | 17.23488 | 0.067886 | −0.04369 |
| 4 | 93 | 24 | 17.234999 | 17.235057 | 0.067886 | −0.04369 |
| 5 | 93 | 24 | 17.235491 | 17.235549 | 0.067886 | −0.04369 |
| 6 | 93 | 24 | 17.235768 | 17.235826 | 0.067886 | −0.04369 |
| 7 | 86 | 24 | 17.235945 | 17.236003 | 0.067886 | −0.04369 |

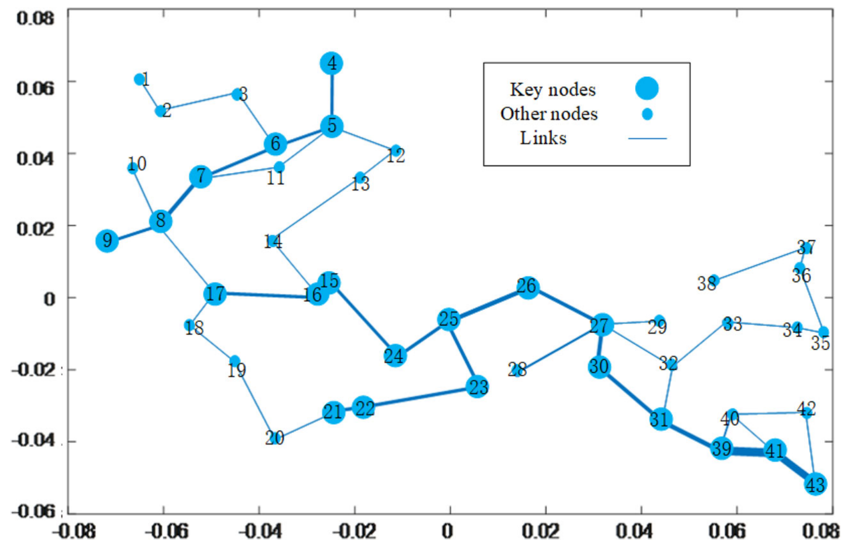



**Fig. 10** The true physical topology of real data

Time, Destination Abscissa, Destination Ordinate, respectively. Our specific approach is to extract the first 10,000 data from the database as raw data, assuming that we only know SrcID and StartTime.

Fig. 10 is the true physical topology of real data, in which the horizontal and vertical coordinates represent the normalized physical location of nodes, and the width of links between nodes represents the strength of links. For convenience, we renumber the nodes, and if there are two nodes communicating for more than 200 times, we consider these two nodes as key nodes. Since we want to find all key nodes, we choose OR rule to make the influence matrix symmetric. At this time, a large number of redundant links will be generated. In order to remove the redundant links, we set corresponding thresholds and get the final results, as shown in Fig. 11.

From the results, most redundant links have been eliminated and all key nodes and strong links have been found. However, what we have to see is that there are some cases of error detection. For example, some redundant links cannot be eliminated even if a higher threshold is set. It's probably because there may be more than one link used in the sensing period and the kernel of Hawkes is too simple to adapt to the complex communication environment.

### 4.4 Comparison with granger causality based method

In this section, we compare the performance of our method with the Granger Causality (GC) based approach described in [13]. The GC definition used in [13] is based on a linear regression formulation. Although the assumptions of GC are

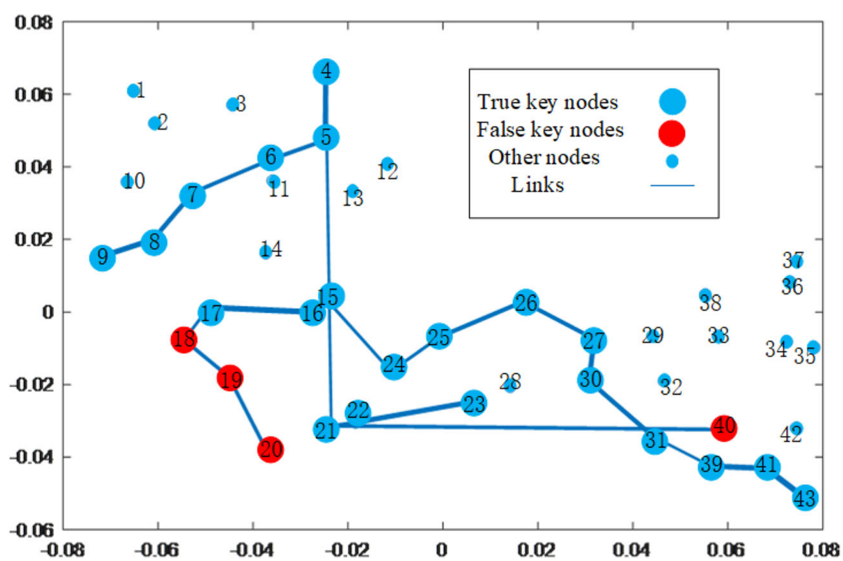



**Fig. 11** Strong topological links of real data under the algorithm that we proposed

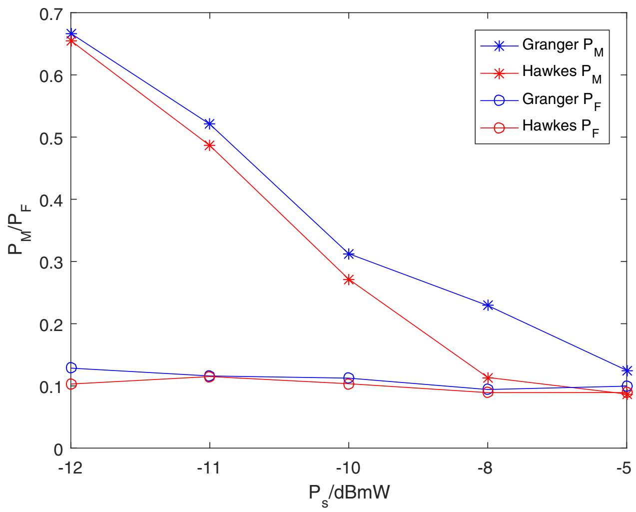



**Fig. 12** The comparisons with Granger Causality based method, in which $N_{event} = 10$, $\lambda = 5 \times 10^{-14}$ W

similar to the Hawkes process, the prior information is not only the start time of transmission, but also the end time of transmission. Therefore, we reduce the prior information of GC to the same as the Hawkes process to make the comparison fair.

The results are shown in the Fig. 12, in which the event number $N_{event} = 10$ and the signal detection threshold $\lambda = 5 \times 10^{-14}$ W. It is observed that the false negative $P_M$ of Hawkes process is lower than GC under the same parameters, especially when the signal transmit power $P_s$ is large. The false positive rate $P_F$ of both two methods presents an unchanging trend. It can be explained by the signal detection threshold. When the threshold is determined, increased signal transmit power makes signal easier to recognize but the noise power is constant. These cause that the $P_M$ and $P_F$ show different characteristics. Even so, it cannot be denied that our method in this paper is superior to the GC based method by synthesizing $P_M$ and $P_F$. Therefore, Hawkes process based method is more suitable in the case of insufficient prior information.

## 5 Conclusion

In this paper, we investigate the issue of wireless network topology sensing with unreliable information caused by imperfect channels. Firstly, we combine topology sensing with wireless channel characteristics for the first time and formulate a robust system model of topology sensing considering unreliable information. Then, we propose a wireless channel-oriented topology sensing scheme based on Hawkes process to address the challenge posed by limited information. In addition, we provide the in-depth simulations under various parameter configurations, which can help us to find a optimal solution in practice. The simulation results suggest that the transmit power and event number are both the parameters that affect performance a lot and the scheme may perform better on distributed topology than centered topology. Finally, we verify the reliability of the scheme by real communication database. The expected research results have been achieved and the predetermined technical requirements have been fulfilled.

At present, the work of wireless network topology sensing is still in its immature stage and there are still many further works to do in the future. This paper has also stimulated many new and interesting research directions, which are worth further research and exploration:

*Communication characteristics.* This paper only simulates the performance in imperfect channels without fading. However, the channel is often more complex and miscellaneous in practice, such as multipath loss, Rayleigh fading or Rice fading. If we want to make the algorithm more practical and robust, the complexity of channel must be increased.

*Selection of adaptive kernel.* One of the most important factors affecting Hawkes process performance is the selection of kernel. In this paper we only use the negative exponential kernel to carry out the simulation, thus results of real data set has an effect bias. In the future, the research on adaptive kernel will be meaningful [35].

*Data fusion.* The case is considered that all the data are received and processed by a single sensor. However, with the popularity of complex networks, it is necessary for sensing to set distributed sensors. At that time, data fusion is one of the major problems faced by distributed sensors [36].

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