Modeling and Analysis of BS Deployment in Multi-scene Urban Areas

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Abstract. With the coming of 5G, the structure of cellular network becomes more and more complex, which provides a great challenge to network modeling. In order to model the real cellular network accurately, researchers proposed many models based on stochastic geometry, such as Strauss process (SP), Poisson hard-core process (PHCP), Thomas cluster process (TCP) and Marten cluster process (MCP). In this paper, we creatively divided the urban areas into three kinds by the indicator of their BS density, which are low-density, middle-density and high-density. Through simulation analysis, we found TCP is more accurate in modeling the low-density city and the middle-density city, while MCP is more accurate in modeling the high-density city.

Introduction

From GSM to 3G, 4G, wireless communication has been developed rapidly. For the upcoming 5G, significantly higher capacity, extremely faster data rates, ubiquitous coverage, and much lower delay are expected. Correspondingly, the structure of cellular network is developing towards ultra-dense, irregular, and multi-scene, where the spatial distribution of the BSs plays an important role in the assessment of the entire networks’ interference and performance. Thus, it is essential to find rigorous and effective models to describe the spatial distribution of BSs under different application scenarios.

As the traditional hexagonal network model cannot satisfy the real network, researchers started to analyze the network interference based on stochastic geometry. Literature [1] proposed that BS distribution can be modeled using the homogeneous Poisson Point Process (PPP). Literature[2][3] proposed that different stochastic geometry models like SP, PHCP, MCP and TCP are fit for BS modeling. Based on those stochastic geometry models, Literature [4] try to find the most suitable one by choosing four different areas—three for city areas and one for rural area, and comparing the accuracy of different spatial models based on statistical identification. Literature [5] analyzed which model is more appropriate for urban areas. In those literatures, the BS density of the urban areas are almost the same, but there are great differences between less developed city and prosperous city, which lead to great differences in BS deployment.

In this paper, we divide city scenarios into three grades, which are suburbs city, less developed city, and prosperous city, according to their real BSs’ density. Then we chose three datasets of real BS data from different areas. By calculating L function and coverage probability, we compare the accuracy of SP, PHCP, MCP and TCP on different areas.

Methodology

Datasets Description

In this paper, we divide the scene of urban areas’ BSs deployment into three kinds, and the difference between them is the density of BSs, which are low-density, middle-density and high-density. In order to analyze which model is more suitable for the particular scene, we use the method of fitting the real BSs deployment with the simulation results. Therefore, we select three groups of real BS data from
OpenCellID [6] representing three scenes, and we name them for city 1, city 2 and city 3. The information of these selected three regions are shown in Table 1.

<table>
<thead>
<tr>
<th>Region</th>
<th>Area[km$^2$]</th>
<th>BS number</th>
<th>BS density[km$^2$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>city 1</td>
<td>1.47*2.22</td>
<td>96</td>
<td>29.417</td>
</tr>
<tr>
<td>city 2</td>
<td>1.17*1.11</td>
<td>157</td>
<td>120.890</td>
</tr>
<tr>
<td>city 3</td>
<td>0.79*0.75</td>
<td>126</td>
<td>212.658</td>
</tr>
</tbody>
</table>

As can be seen from Table 1, the density of three city areas ranges from 29.417 to 212.658, which is clearly divided into three levels. Moreover, the location of the BSs are shown in Fig. 1. Fig. 1 (a) represents the low-density city, Fig.1 (b) represents the middle-density city and Fig.1 (c) represents the high-density city.

![Figure 1. BS locations of four regions. (a) city 1. (b) city 2. (c) city 3.](image)

**Fitting Method**

Since there are three groups of real BS data and four candidate models, the next move is to find an appropriate way to link them. In this paper, likelihood-based method is used. It is a common method in the analysis of stochastic geometry, and there are several kinds of likelihood methods, such as maximum pseudo likelihood, maximum profile pseudo-likelihood, composite likelihood and palm likelihood. In our simulation, maximum pseudo likelihood method is used in fitting Poisson Hardcore process, maximum profile pseudo likelihood method is used in fitting Strauss process, and composite likelihood method is used in fitting Thomas cluster process and Marten cluster process.

**Evaluation Statistics**

After fitting on real BS data, we can get the parameters of each stochastic geometry model, which can generate the distribution of simulation BSs. It is essential to find proper evaluation statistics on characterizing the performance of those simulation results. Generally, there are several kinds of methods, and in this paper, Besag-Ripley’s L function [7] and coverage probability are used.

L Function was proposed by Besag based on Ripley’s K-function. It is an effective statistic widely used in analyzing spatial point process. L-function can be described by Eq. 1:

\[
L(r) = \sqrt{\frac{K(r)}{\pi}}
\]

where \(K(r)\) is the Ripley K-function of a spatially homogeneous point pattern, and it can be described by Eq. 2:

\[
K(r) = A \sum_{i=1}^{n} \sum_{j=1}^{n} \delta_{ij}(r) \frac{1}{n^2}
\]

where \(A\) is the area of the window; \(n\) is the number of points; \(r\) is the spatial scale; \(r_{ij}\) is the distance between point i and point j, while \(r_{ij} \leq r, \delta_{ij}(r) = 1, \text{ else } \delta_{ij}(r) = 0\).

Coverage Probability means the probability that a user's signal-to-noise ratio is higher than the threshold in a region. Generally, a user accesses the BS with the maximum received power, and
signals received from other BSs are interference. In this paper, we consider the path loss exponent $\alpha$ as 4, the Rayleigh fading as 1, and we ignore the effect of shadow fading and noise. Therefore, the coverage probability can be calculated as Eq. 3:

$$SINR = \frac{P_d(s,r)^{-\alpha}}{\sum_{i \in Z^r} P_d(s,i)^{-\alpha}}$$

(3)

where $s$ is the location of the user; $P_r$ is the transmit power of the accessed BS; $P_i$ is the transmit power of other BSs.

Simulation and Analysis

L-function

For each dataset, we first fit it with the four models using R software\cite{8}, from which the corresponding parameters of each model can be obtained. With these parameters, we generate the distribution of simulated BSs by using the Monte Carlo simulation method. In this paper, we did 39 simulations for each model. Then, the L-function of each distribution can be calculated. Among them, there are maximum and minimum values of L-function, which gives the upper and lower envelopes. Based on the L-function, we can initially determine whether the model is suitable or not.

Following the above method, we fit the three datasets with the SP, PHCP, THCP and MCP. The parameters of each model are in Table 2.

<table>
<thead>
<tr>
<th>Region</th>
<th>Model</th>
<th>SP</th>
<th>PHCP</th>
<th>TCP</th>
<th>MCP</th>
</tr>
</thead>
<tbody>
<tr>
<td>city 1</td>
<td>$\beta=29.26$</td>
<td>$\beta=28.45$</td>
<td>$k=45.30$</td>
<td>$k=46.271$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\gamma=0.992$</td>
<td>$r=0.0085$</td>
<td>$r=0.055$</td>
<td>$r=0.101$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r=0.26$</td>
<td></td>
<td>$\mu=0.651$</td>
<td>$\mu=0.636$</td>
<td></td>
</tr>
<tr>
<td>city 2</td>
<td>$\beta=91.74$</td>
<td>$\beta=120.05$</td>
<td>$k=27.59$</td>
<td>$k=28.84$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\gamma=0.998$</td>
<td>$r=0.0054$</td>
<td>$r=0.063$</td>
<td>$r=0.115$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r=0.3$</td>
<td></td>
<td>$\mu=4.382$</td>
<td>$\mu=4.191$</td>
<td></td>
</tr>
<tr>
<td>city 3</td>
<td>$\beta=74.67$</td>
<td>$\beta=214.36$</td>
<td>$k=26.71$</td>
<td>$k=27.31$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\gamma=1.072$</td>
<td>$r=0.0029$</td>
<td>$r=0.031$</td>
<td>$r=0.058$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r=0.13$</td>
<td></td>
<td>$\mu=8.059$</td>
<td>$\mu=7.882$</td>
<td></td>
</tr>
</tbody>
</table>

For city 1, as can be seen from Fig. 2, Both TCP and MCP fit the real points well, because the whole line of the real points lie within the envelope, and the envelope of TCP is wider than MCP. As for SP and PHCP, most of their lines lie within the envelope. However, in Fig. 2 (a), when $0.05< r <0.2$ and $0.22< r <0.235$ the line of the real points is above the upper bound of the envelope, and in Fig. 2 (b), when $0.11< r <0.17$, the line of the real points is above the upper bound of the envelope. As there is more region outside the envelope, we can say that PHCP fits better than SP.
Fig. 3 shows that both TCP and MCP fit the real points of city 2 well, because the whole line of the real points lie within the envelope, and the envelope of MCP is wider than TCP. As for SP and PHCP, only small part of their lines lie within the envelope, which means both of them cannot fit the real points well.

![Figure 3. L-function of simulated models fitting on city 2. (a) SP. (b) PHCP. (c) TCP. (d) MCP.](image)

In Fig. 4, we can get similar discovery. The whole line of the real points lie within the envelope of TCP and MCP. On the contrary, almost whole line of the real points lie outside the envelope of SP and PHCP. In addition, Table 2 shows that the parameter γ of SP is 1.072, bigger than 1, which means that the real points cannot be fitted by SP. In addition, PHCP fits the real points badly.

![Figure 4. L-function of simulated models fitting on city 3. (a) SP. (b) PHCP. (c) TCP. (d) MCP.](image)

**Coverage Probability**

Then, in order to compare the coverage probability between the real BSs and the four models, we generate 1000 sets of BS data for each model. For each simulated region, we randomly generate a user in it for 100 times, while we randomly generate a user in the real region for 10^5 times. At last, we set the threshold range from -10 dB to 20 dB stepped by 0.5. By using the Monte Carlo simulation method, the coverage probability is given.

As can be seen in Fig. 5 (a), the five lines are very close. Roughly speaking, the line of SP and PHCP almost coincide, so do the line of TCP and MCP. Precisely speaking, the line of real points is closer with the line of TCP and MCP. Combined with the L-function above, we can conclude that MCP fits city 1 best.

Fig. 5 (b) shows that the coverage probability of SP and PHCP are almost the same, and they are obviously higher than the TCP and MCP. In addition, line of the real is closer with the line of the MCP. Combined with the L-function, it seems MCP fits city 2 best.

The conclusion we can conclude from Fig. 5 (c) is apparent. The line of TCP is closet with line of the real, and TCP fits city 3 best. The coverage probability of SP and PHCP is much higher than that of TCP, MCP and real, which comes from the distribution of the BSs. city 3 represents the scenery hotspot areas, where is in urgent need for network capacity. Therefore, many BSs were put in the small region, which conclude the high capacity of part of the area and the lower coverage probability overall. The line of TCP is closer with line of the real, and TCP fits city 3 best.
Conclusions
In this paper, we analyze the performance of four stochastic geometry models, which are SP, PHCP, TCP and MCP, based on three real BS datasets with different density. Through the above simulation, we conclude that TCP and MCP have a good performance in three kinds of areas. In addition, MCP performs better than TCP in low-density cities and middle-density cities, while TCP performs better in high-density cities. As for SP and PHCP, the coverage probability of their simulation is higher than real, TCP and MCP, especially in middle-density and high-density cities. Combined with the L-function, we can conclude that they did not fit city sceneries well.

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References