SHORT-PAPER

Understanding Deployment Experience of 5G

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ABSTRACT

The global rollout of 5G mobile networks has prompted discussions on deployment strategies. Given the knowledge gap in the current deployment strategies of 5G base stations, understanding the deployment experience from regions with widespread 5G base stations is valuable for guiding future deployments elsewhere. In this study, based on a large dataset collected from a metropolitan city in China, we discover the misalignment between 5G traffic demand and the number of base stations. Then we introduce a factor to quantify the misalignment. Our analysis indicates the following important observations. Firstly, unique traffic patterns of functional areas contribute to different misalignment factors, i.e., transport areas exhibit a positive factor, in contrast to the negative factor observed in urban comprehensive and residential areas. Secondly, regions with a high density of base stations still suffer from low energy and resource utilization efficiency due to their high energy consumption. Thirdly, our analysis reveals that 5G base stations are frequently located in areas with large 4G traffic, yet the incomplete migration of traffic to 5G results in misalignment. This understanding of the 5G deployment experience can help further studies on optimizing energy efficiency and network utilization rate of the mobile networks.

CCS CONCEPTS

• **Networks → Network measurement**.

KEYWORDS

Cellular traffic; traffic-base station misalignment; base station deployment; energy efficiency

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1 INTRODUCTION

China has seen rapid advancements in 5G mobile network where approximately 3 million 5G base stations have been deployed by June 2023 [11]. Moreover, by the end of 2022, China's 5G users exceeded 561 million, accounting for over 60% of the global total [4]. This surge is driven by the increasing need for mobile-reliant applications [10], due to the benefits of 5G in data rates, reliability, and energy efficiency.

However, several challenges exist in the deployment of 5G base stations. Firstly, building 6 million 5G base stations across China is estimated to take seven years and cost between 1.2 to 1.5 trillion yuan [2]. Short range and low penetration of 5G frequency bands requires significant infrastructure for broad coverage [9]. Secondly, the overall power consumption of 5G could be 12 times that of 4G networks [5]. Growing concerns over energy-related pollution have intensified the focus on improving energy efficiency [6, 12]. Thirdly, 4G and 5G have diverse deployment strategies [3], while unique traffic patterns in different functional areas [13] add further complexity to the transition from 4G to 5G.

The constraints result in unevenly distributed 5G base stations and a network that struggles to meet capacity, availability, energy, and cost efficiency requirements [7]. Understanding 5G deployment is essential for solving those challenges [1], helping ISPs in cost reduction and network efficiency optimization, benefiting mobile users. Nevertheless, current knowledge gaps exist regarding the deployment status of 5G base stations. Moreover, we also lack knowledge in terms of the alignment between the deployed 5G base stations and the traffic demand, the degree of misalignment, and the underlying causes of the misalignment. Practical experience from real-world data of 5G networks is missing for a comprehensive understanding of these issues.

In this paper, based on a credible dataset that covers 14,243 base stations in Nanchang, a metropolitan city in China, we make the following contributions:

- We conduct an empirical study of a large-scale real-world dataset of 5G networks, and introduce a factor to measure the misalignment between the traffic demand and the number of base stations, uncovering their spatio-temporal distribution and their unique patterns in different funcional areas.
- We analyze the relationship between the misalignment factor and the energy efficiency, as well as the usage ratio of physical resource block, and offer insights into the inefficiency of the current 5G network, i.e., regions with negative misalignment factors serve as a primary cause for the current inefficiency.
- We conduct further analysis on the influence of 4G traffic on the 5G misalignment factor to show that prioritizing 5G base stations in high 4G traffic areas causes negative misalignment factors.

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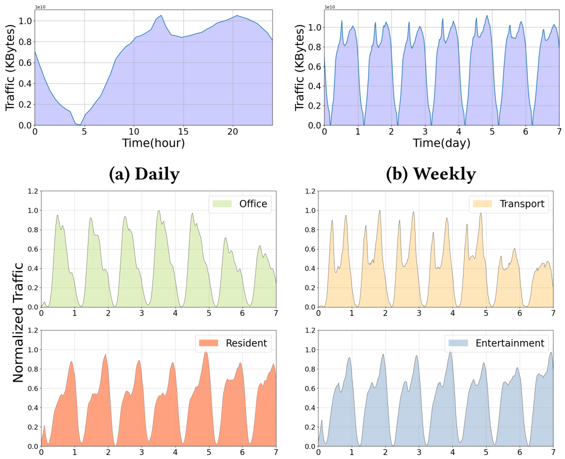


(a) Daily (b) Weekly

(c) Functional areas

Figure 1: Temporal distribution of 5G traffic.

2 VISUALIZED ANALYSIS OF SPATIAL DISTRIBUTION

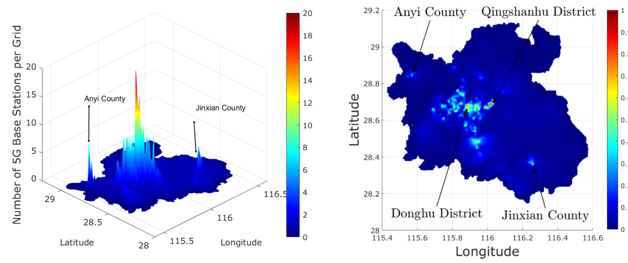
2.1 Dataset Description and Preprocessing

The dataset was collected from the cellular network in Nanchang, in collaboration with a telecom operator. Nanchang is a city that covers an area of 7,195 square kilometers and has a permanent resident population of 6.5381 million. The fine-grained dataset was collected every half hour over a week in May 2022 and contains 14,243 base stations, including records of base station ID, geographical coordinates, traffic volumes, usage ratio of physical resource block (PRB), average power for base band units (BBUs), remote radio units (RRUs), and air-conditioning systems. It offers a nuanced view into the mobile networks and enhances the results credibility.

We subdivide the area of Nanchang, which spans from latitude 28.0° to 29.2° and longitude 115.4° to 116.6°, into a grid of mesh regions with granularity of 0.01°. The number of base stations and traffic are computed in each mesh region, enabling a detailed investigation of network coverage.

2.2 Temporal and Spatial Distribution of 5G

Our analysis begins with the temporal distribution of 5G traffic across the entire network. Given that the traffic data is collected in thirty-minute intervals, the timeline of each day is segmented into 48 slots. Fig. 1 depicts the temporal distribution of 5G traffic across different timescales and functional areas. Daily pattern exhibits two peaks around 12PM and 8PM and a trough at 4AM, corresponding to the inactive period of 5G base stations. Weekly pattern exhibits a repetition of daily pattern. Weekly patterns are different in 4 typical functional areas: office, resident, transport, and entertainment areas. Office areas experience highest traffic during work hours, and lower traffic on weekends. Residential areas peaks at 8PM when people are at home. Transport areas, including transit hubs, exhibit peaks during rush hours at 9AM and 5PM. Entertainment areas like shopping malls typically peak at lunchtime and dinnertime.



(a) Number of 5G base stations (b) Normalized 5G traffic

Figure 2: Spatial distribution of 5G base stations and traffic in Nanchang.

We then plot the spatial distribution of 5G base stations and the normalized 5G traffic in Nanchang. As shown in Fig. 2, both distributions exhibit highest density in the city center, and also show notable peaks in Jinxian and Anyi counties. Lower population density and incomplete 5G infrastructure in county areas result in reduced traffic demand.

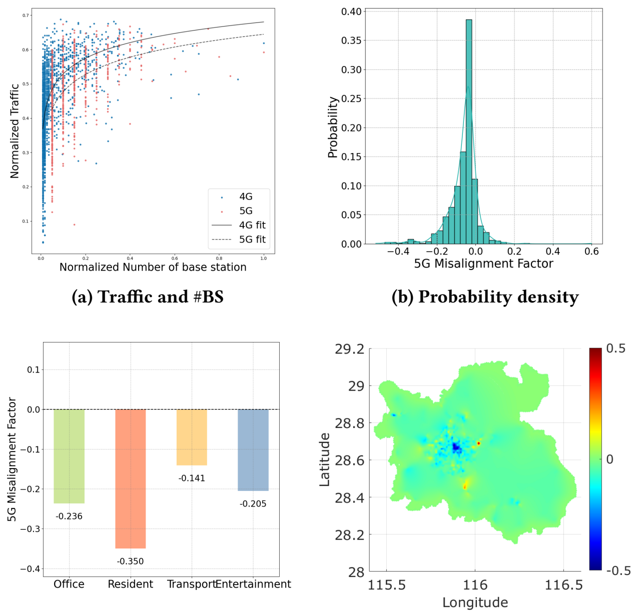
2.3 5G Base Station Distribution and Traffic Demand

The deployment strategy of base stations is closely linked to the demands of network traffic. It is obvious that areas with higher traffic volumes indicate a larger need for network services. To evaluate the current deployment strategy, we analyze the correlation between network traffic and the number of base stations in Fig. 3(a). While there is a generally positive correlation for both 4G and 5G networks, this trend does not uniformly apply for all regions. Regions with the same number of base stations often experience different traffic volumes, indicating a misalignment. Under the presumption of positive correlation, we introduce a misalignment factor represented by

$$F = \frac{L_{\mathrm{i}}}{max(L_{\mathrm{i}})} - \frac{n_{\mathrm{i}}}{N_{\mathrm{max}}}, \tag{1}$$

where L_{i} and n_{i} represent the traffic and base stations number in each region respectively. $max(L_{\mathrm{i}})$ and N_{max} denote the maximum traffic and the largest number of base stations across all regions. Our assumption posits that regions with more base stations should exhibit larger traffic demand, although the presence of the maximum base stations number does not guarantee the highest traffic. F around 0 signifies the alignment. $F < 0$ indicates base stations adequately meet traffic demand, while $F > 0$ implies insufficient base stations. The last two situations both indicate misalignment. The histogram of 5G misalignment factor in Fig. 3(b), ranging from -0.5 to 0.2, shows over half of F fall within the range of -0.25 to 0, indicating well-aligned in their 5G deployments. We focus on areas with higher absolute values of F, as they represent a strong misalignment between traffic demand and base station resources.

Degree of misalignment correlates with different functional types. As shown in Fig. 3(c), transport area has a biggest F while residential area exhibits a smallest F. According to observations of more than 40 regions selected from Fig. 3(d), urban comprehensive (areas including 3 or more functional types) and residential areas mostly have negative F, in contrast to positive F in transport and



(a) Traffic and #BS **(b) Probability density**

(c) Different functional areas **(d) Spatial distribution**

Figure 3: Visualization of the distribution of 5G misalignment factor (F) from different perspectives.

comprehensive areas in county. Significant day-to-night population fluctuations increase traffic demands, leading to a positive F as data traffic demand exceeds supply.

3 INFLUENCE ON ENERGY AND RESOURCE EFFICIENCY

3.1 Energy Efficiency

Energy efficiency and resource utilization efficiency are important parameters to measure the utilization ratio of base stations. The energy consumption of base stations contributes a lot to the mobile network. High energy consumption of base stations will lead to environmental problems. Taking into account the primary components of base stations, such as the communications subsystem, which encompasses the Base Band Unit (BBU) and the Remote Radio Unit (RRU), along with the cooling devices, the energy consumption of a base station can be modeled as follows:

$$P_{\text{bs}} = P_{\text{tx}} + P_{\text{cooling}}, \tag{2}$$

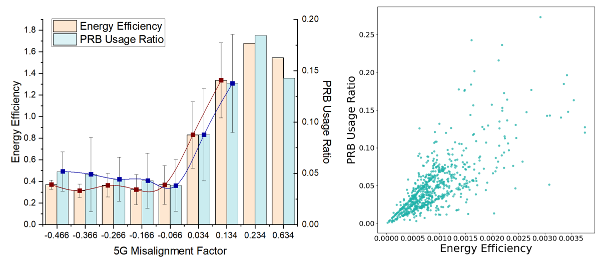
$$P_{\text{tx}} = P_{\text{BBU}} + P_{\text{RRU}}, \tag{3}$$

$$E = P \cdot t \cdot 10^{-6}, \tag{4}$$

where P_{BBU}, P_{RRU}, and P_{cooling} represent the average power of BBUs, RRUs, and the average power required for air-conditioning to maintain the proper operating temperature, respectively. The energy consumption E, measured in MWh, can be calculated from power data expressed in watts.

To measure the amount of cellular traffic that can be provided per unit of energy consumption, we use energy efficiency, which is denoted as $\eta = \frac{L}{E}$, where L represents the traffic load. Therefore, in areas where base stations are relatively sufficient to the demand (F<0), we tend to assume that its energy efficiency is also high. However, in practice, the energy efficiency of base stations may still be lower.

As shown in Fig. 4(a), regions with negative F have lower energy efficiency compared to those with a positive F, indicating that traffic processing in regions with sufficient base stations still requires relatively high energy consumption. As F increases, in areas where traffic is dense and the number of base stations is limited, each base station handles a higher volume of traffic, leading to a higher energy efficiency.



(a) Energy efficiency, PRB usage ratio and F **(b) PRB usage ratio and energy efficiency**

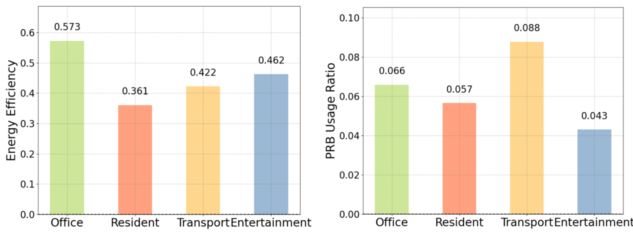
Figure 4: Correlations between energy efficiency and F, PRB usage ratio and F.

3.2 PRB Usage Ratio

PRB usage ratio is the fraction of used PRBs to the total PRBs at a base station, reflecting its resource utilization. The ratio can also be calculated by L/C [8], where C is the capacity of base station. As shown in Fig. 4(a), negative F has relatively low PRB usage Ratio. Since the energy efficiency and the PRB usage ratio are related to the energy and spectrum resource of a base station respectively, it is worth understanding the correlation between them. Fig. 4(b) suggests that high PRB usage ratio can lead to higher energy efficiency, as it means the network is handling traffic effectively without wasting spectrum or energy resources. However, the practical relationship still needs the consideration of traffic patterns caused by different functional areas. Fig. 5 depicts energy efficiency and PRB usage ratio in different functional areas. It suggests that functional areas with the highest energy efficiency may not have the highest PRB usage ratio, and vice versa.

4 IMPACT OF NETWORK TRAFFIC

Regions with negative F are associated with low energy efficiency and low PRB usage ratio. This association underscores the importance of investigating the causes behind these diminished factors. Given that the rollout of 5G relies on existing 4G base stations, understanding the influence of the 4G network on 5G misalignment factor is essential. We first plot the correlation between 4G traffic and 5G misalignment factor in Figure 6(a). The result suggests that regions with higher 4G traffic are more likely to exhibit both negative and positive 5G misalignment factors with large absolute values, which diminish in areas where 4G traffic is lower. Furthermore, we analyze the correlation between 5G traffic and



(a) Energy efficiency **(b) PRB usage ratio**

Figure 5: Energy efficiency and PRB usage ratio in functional areas.

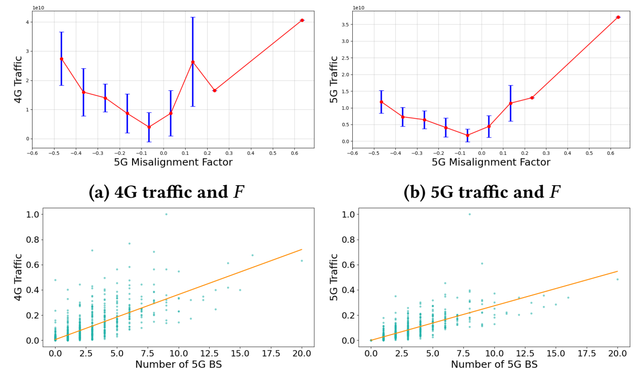
the 5G misalignment factor, as depicted in Figure 6(b). The trend indicated in Figure 6(b) is less pronounced than that in Figure 6(a), particularly when the 5G misalignment factor is negative.

To determine the underlying reasons for the smaller misalignment factor in those regions, we then consider the impact of both 4G and 5G traffic on the number of 5G base stations, which can directly reflect the deployment of 5G base stations. Fig. 6(c) and Fig. 6(d) show the correlation of 4G and 5G traffic with number of 5G base stations, respectively. Slope in Fig. 6(c) is steeper than that of Fig. 6(d), indicating that 4G traffic in a region has a stronger positive correlation with the number of 5G base stations. It reveals a fact that 5G base stations are more likely to be deployed in regions with high 4G traffic volumes, causing a large n_i in the factor. However, not all traffic in those areas migrates to 5G, resulting in L_i not being proportional to n_i. Therefore, it will lead to a negative F, as well as poor energy efficiency and resource utilization efficiency of 5G base stations.

5 CONCLUSION AND FUTURE WORK

In this paper, we discuss the misalignment between the number of base stations and traffic demand based on a large-scale dataset and introduce a factor to quantify this misalignment. Then we analyze its spatial distribution in the city, as well as the relationship with energy efficiency and PRB usage ratio. Our findings suggest that areas with negative misalignment factor, which means the base stations can meet the traffic demand, may also suffer from low energy efficiency and low PRB usage ratio. The cause of a negative misalignment factor can be attributed to the prioritized deployment of 5G base stations in high 4G traffic regions.

Our future work will focus on developing a deployment model which can help balance the misalignment factor with energy efficiency and PRB usage ratio in different regions, in order to achieve a misalignment with smaller absolute value accompanied by a relatively high energy efficiency and high PRB usage ratio. We plan to use this model to help optimize network usage and enhance the overall energy efficiency in mobile networks.



(a) 4G traffic and F **(b) 5G traffic and F**

(c) 4G traffic and 5G #BS **(d) 5G traffic and 5G #BS**

Figure 6: Impact of network traffic on F.

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