Cellular Service with Settlement-Free Peering

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***Abstract*—Despite several iconic innovations in wireless networks, cellular service still remains largely unreliable with regards to non-urban network coverage. Cellular providers often need to make roaming agreements among each other for serving their customers with basic connectivity in areas where they do not have coverage. Considering all the technical limitations of domestic roaming, we present a "wireless peering" model for *settlement-free* spectrum sharing. It allows providers to extend their coverage to "off-network" regions without any hardware modifications. Its software-defined nature makes the model highly scalable, easy to deploy and cost-effective. Simulation results show a significant improvement in off-network wireless speed, data allowance, and network coverage as well as increase in provider revenue when compared to roaming.**

***Index Terms*—Spectrum Policy, Peering, Roaming, Opportunistic Access, Cellular Networks, Resource Allocation.**

I. Introduction

Cellular providers have low motivation to expand their infrastructure to non-urban areas, because of an imbalance between the required investment and monetary return. Only 19% of the entire United States (US) population lives in rural areas, which comprise approximately 95% of the total US land mass [1]. As a result, people living in or visiting rural and remote areas suffer from inferior Quality-of-Service (QoS) [2]. We propose an architecture that enhances end-user experience by allowing service providers to "peer" and share the already-established Base Stations (BSs) to serve each others' customers. Customers can get cellular service in areas where peered providers have coverage without any off-network restrictions, such as a reduction in allowed call times, lower access speeds, or decreased data caps. As a long-term effect, cellular providers will be highly motivated to improve their service in low-population areas due to the implicit incentives in the form of improved service for their customers elsewhere.

A. What is Peering?

Peering is a well-known concept among Internet Service Providers (ISPs) in the wired Internet market [3]. It enables connecting and exchanging network traffic among Autonomous Systems (ASes) directly without paying to transit ISPs or relying on a third-party service. While the technical details vary depending on the different types of peering, the core idea remains the same: collaboration among providers [4]. Settlement-free peering enables ISPs to share their resources and reciprocally serve each other's customers. Among other benefits, peering improves the end-user experience by reducing network congestion and end-to-end latency and helps ISP admins reduce transit costs.

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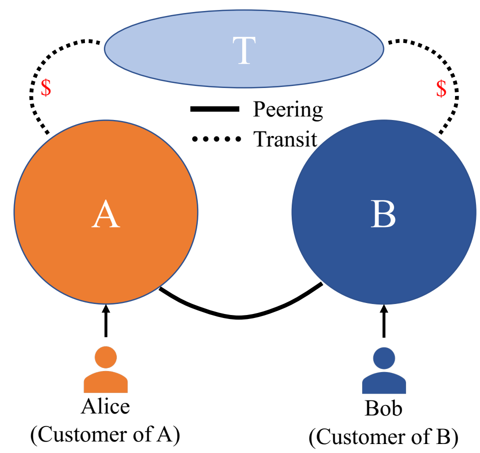


Fig. 1: Alice and Bob can connect using a transit link through AS T or directly using a peering link. Transit link implies a payment to the transit ISP.

We explain the peering benefits among two ISPs each having an AS. In Fig. 1, customers of AS A can reach customers of AS B by paying AS T for a transit link ($A \rightarrow T \rightarrow B$). Another option is to directly use a settlement-free peering link ($A \rightarrow B$). For AS A, peering with AS B will be economically beneficial if the monetary cost of the peering link is lesser than the cost of using transit link [5]. We define $\rho^t_{A\rightarrow B}$ as the *transit cost* of sending traffic from AS A to AS B via AS T, which includes the money transit provider T charges A for carrying its traffic to B. We define $\rho_{B\rightarrow A}$ as the *peering cost* of receiving traffic from AS B to AS A which includes the indirect costs incurred on A because of handling B's traffic. If $\rho_{B\rightarrow A} < \rho^t_{A\rightarrow B}$, AS A will be willing to peer with AS B. In order for a peering relationship to be viable, a reciprocal situation should be happening for B, i.e., $\rho_{A\rightarrow B} < \rho^t_{B\rightarrow A}$. If these willingness conditions are satisfied for both A and B, then establishing a peering relationship reduces the social cost associated with carrying two-way traffic between A and B, since $\rho_{A\rightarrow B} + \rho_{B\rightarrow A} < \rho^t_{A\rightarrow B} + \rho^t_{B\rightarrow A}$ will also satisfy.

B. Contributions

We introduce the concept of *wireless peering* by drawing motivation from ISP peering in wireline networks and designing a model using the same core ideas in cellular service providers. In particular, this paper makes the following key contributions: **(1)** Design a light-weight and effective peering model for wireless networks that is easy to deploy; **(2)** Define

Customer Satisfaction Score (CSAT) for quantifying the effect of change in cellular QoS; **(3)** Formulation of a wireless peering optimization problem to select the best places to peer for a cellular provider; **(4)** Proof of NP-hardness of the peering optimization problem and design of heuristic solutions; and **(5)** Design a cellular network simulation model which we use for evaluating the proposed peering model and heuristics.

The rest of the paper is organized as follows: In §II, we provide background for the proposed wireless peering concept, cover the related works and state-of-the-art policy/mechanisms on incentivizing collaboration among cellular providers. Next, in §III, we detail our proposed wireless peering model and compare it with the existing roaming framework. Then, in §IV we formalize the proposed peering model, define the peering optimization problem for selecting the best places to peer, show the NP-hardness of the problem, and design heuristics to solve it. §V details our procedure to gather a realistic data set on base station locations, design a simulated cellular network, and evaluate the heuristics using the simulation. Finally, we conclude our work in §VI.

II. Background and Motivation

Incentivizing competitor service providers for collaboration to increase larger good (e.g., better overall QoS to users and reduced social cost) has been a challenge tackled in several markets, particularly where the service being provided to the users require multiple providers to cooperate. Network service provisioning is, arguably, the most fitting case for this scenario. No single provider's infrastructure can cover every location in the world or a country. Hence, the providers should cooperate in providing a service with large enough coverage and quality acceptable to their users. However, due to the competitiveness of business goals, the providers still need effective mechanisms that provide healthy markets for sharing.

A. Existing Models of Inter-Provider Collaboration

The research community has investigated various methods for leveraging benefits of roaming to improve customer experience. The work done in [6] is about a global mobility management framework for supporting seamless roaming across wireless networks. Most local providers in the US have contracts to provide domestic roaming services to their customers, which is generally included with most cellular plans at no additional fee. However, on the user end, domestic roaming providers often impose various restrictions on aliens (i.e., subscribed to another provider) customers [7]–[10]. [11] proposed an improvement of mobile data services by implementing public wireless LANs for supporting inter-operator roaming. In addition, the authors investigate Subscriber Identity Module (SIM) and web-based authentication methods for current and occasional users.

The government reward-based model is one way for promoting spectrum sharing among competitors. Some models employ game-theoretic approaches and use auctions in dynamic spectrum sharing [12], [13]. In [14], the authors devise two models: (1) the government allows access to federal bands as 'reward spectrum' to the operator, and (2) the government provides infrastructure support. Similar work has been done by Tang et al. in [15]. Reward-based spectrum sharing models usually require providers to adhere to regulations set by a third party, which may cause providers to lose interest in the agreement. Our wireless peering proposal tends to eradicate this problem where no third party is involved. The providers can peer among themselves for their mutual benefits (revenue maximization) and ensure that the customer satisfaction levels are maintained or exceeded.

A plethora of inter-provider spectrum sharing policy mechanisms has been studied that involve device-level coordination. A real-time spectrum auction framework for distributing spectrum among a large number of users under interference constraints was discussed in [16]. Their method can achieve conflict-free spectrum allocation, which increases spectrum utilization and maximizes auction revenue. [17] showed a non-cooperative game framework to share the licensed spectrum among devices subscribed to different providers.

B. Pros and Cons of Wireless Peering

Wireless peering refers to a settlement-free exchange of service. An increasing number of wired ISPs have established peering relationships. However, to our best knowledge, no work has been done on wireless peering. Unlike wired ISPs, the cellular market is designed in a very competitive manner, and any collaboration among providers comes with stringent rules and hefty payments. We propose a lightweight model that is effective in allowing providers to collaborate. Customers can benefit from an improved QoS in both in-network and out-of-network areas. Since the cellular market is private, the major driving forces for innovation are customer contentment and retention, which translates into an increase in revenues and profits in the long run. Wireless peering allows users to automatically join a secondary provider in case their primary provider is not available. It increases customer trust on the provider and overall satisfaction. From a provider's point of view, peering costs nothing extra and is flexible enough to employ a trial and error approach for optimal contract formation. Nonetheless, in this paper, we discuss in detail what aspects affect optimal area selection for peering.

Peering can cause congestion in densely populated areas, which require additional infrastructure for decent provisioning of cellular services like temporary software optimizations, e.g., *radio resource allocation tuning* and *opportunistic connection sharing* for large scale events [18]. Moreover, peering in highly volatile traffic areas may result in overloaded BSs due to a high volume of customers, causing connection failures and poor QoS. Another glaring problem is *free-riding*. Customers can knowingly or unknowingly subscribe to the cheaper provider option but continue using a peering connection from a different provider. Similar to recent works, e.g., [19], our wireless peering model also has room for exploitation from free-riders. One solution to this problem can be peered cellular providers' agreement not to serve each others' customers other than the agreed-upon locations. This will give a leeway for

TABLE I: Symbols and Notations

Symbol	Description	Symbol	Description
$\mathcal{T}$	Set of counties	$\mathcal{K}$	Set of customers
N	Number of counties	K	Number of customers
α_{ji}	Provider j's network coverage area in county i	C_{ji}	Provider j's network coverage score in county i
S_k	Customer k's speed score	Q_k	Customer k's signal score
σ_k	Customer k's CSAT	T_i	Total area of county i
$\mathcal{P}$	Set of cellular providers	r_{XY}	Roaming fee from provider X to Y
R_x	Provider x's total Revenue	f_x	Provider x's avg. subscription fee

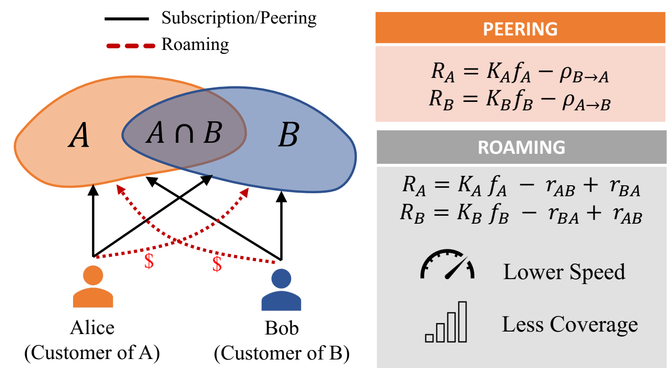


Fig. 2: Alice and Bob can connect to visiting provider B and A respectively using either roaming or peering.

the providers to indirectly control free-riding possibilities. However, designing mechanisms to directly control free-riding at large scales (i.e., millions of users) is a complex problem that needs to be solved for any policy framework which enables pervasive spectrum sharing [20] among operators.

III. Wireless Peering: Basics and Concepts

We describe wireless peering from the point of view of users and providers, and compare it with roaming. Figure 2 illustrates two users, Alice and Bob, who can connect to their home provider using the default subscription link. Also, they can get service outside of the home provider using either a peering link or a roaming link:

- *Service via Roaming:* If Alice connects to B's BSs using a roaming connection, this does not explicitly cost Alice anything[1]. However, there is an associated *cost* that A has to pay B, which eventually gets (indirectly) reflected on Alice's bill as A has to recover the roaming expenses.
- *Service via Peering:* If Alice connects to B's BSs via peering, this costs nothing to her. Due to a settlement-free peering agreement between A and B, A does not have to pay any fees to B. In our proposed peering framework, if users travel to outside of home network, they get treated as a *primary user* by the peered providers, and none of the restrictions mentioned in Figure 2 are applied to them. We have summarized different restrictions that carriers often impose on roaming services in Table II.

[1]In most countries, roaming fees to users do not exist anymore.

TABLE II: U.S. Domestic Roaming Restrictions [7]–[10]

Provider	Speed	Data Allowance
At&t	2G	100 MB/mo
Verizon	2G/3G	-
T-Mobile	2G	200 MB/mo
Sprint	2G	200 MB/mo

Roaming is primarily about improving coverage, while peering goes beyond it and addresses other components that affect QoS. In addressing issues of strengthening coverage and the QoS received by customers, peering can incentivize collaboration among the providers without additional costs. In this work, we aim to outline a framework for establishing effective peering contracts for wireless providers. A can extend its coverage via a roaming agreement with B in areas that it covers. This incurs roaming costs, as we discussed above. In a typical roaming agreement, B does not have to serve all users of A if B's network is highly congested. However, in the case of wireless peering, both providers will treat each others' customers as primary users and will not charge any fees. Hence, in peering, there will be an additional implicit cost of serving peer users.

In the case of roaming, let us define r_{AB} as the roaming cost A has to pay B for allowing A's users to connect to B's network. Similarly, r_{BA} can be defined as the roaming fees that B has to pay A for allowing B's users to connect to A's network. In peering, we can define the additional cost incurred by A for handling B's users as $\rho_{B\to A}$. This can include multiple direct and indirect costs, like additional power consumption or additional congestion on A's network. Similarly, we can define the additional cost incurred by B for handling A's users as $\rho_{A\to B}$. Now, in a fashion similar to wireline peering (§I-A), if $\rho_{B\to A} < r_{AB}$, it means the cost of handling B's users is lower than the roaming cost and therefore A will be willing to peer with B. In order for such a peering relation to be viable, a reciprocal situation should be happening for B, i.e. $\rho_{A\to B} < r_{BA}$. If these conditions are satisfied for both A and B, then establishing a peering relationship reduces the social cost associated with roaming since $\rho_{A\to B} + \rho_{B\to A} < r_{AB} + r_{BA}$. This holds only under the assumption that providers have enough capacity to handle additional users, which we will discuss in the sequel.

The effect of peering and roaming on the total provider revenue can be formulated using the equations given in Fig. 2. Assume, provider A has K_A customers, and each of them is charged a monthly subscription fee, f_A. Similarly, K_B and f_B are defined for B. Thus, provider A and B generate revenues $K_A f_A$ and $K_B f_B$, respectively, from subscription fees. If both maintain a roaming agreement, their overall revenues depend on costs they pay to each other, i.e., $R^r_A = K_A f_A - r_{AB} + r_{BA}$ and $R^r_B = K_B f_B - r_{BA} + r_{AB}$. However, if A and B form a peering agreement, their revenues will be $R_A = K_A f_A - \rho_{B\to A}$ and $R_B = K_B f_B - \rho_{A\to B}$.

The peering cost due to handling peer's users, i.e., $\rho_{B\to A}$

for A, depends on many factors. The most important of which is the number of peer users one has to serve. It depends on the sizes and coverage of the peering providers, which we will discuss shortly in §III-A. Intuitively, the peering cost on the individual providers will be near zero if they have enough capacity to handle the peer's users. In such cases, $R_A < R_A^r$ if A has large enough idle capacity to serve B's users since $\rho_{B \to A} \to 0$. From a policy standpoint, this revenue model also motivates the providers to increase their capacity at areas where the peer's customers are more likely to appear, which eventually leads to an increase in the total coverage of all providers. However, it is also possible that the peering cost may become unacceptable by the providers if the number of users from the peer is too large. There are two ways a provider can control the peering cost according to our peering framework: (1) By properly selecting a provider to peer and (2) By negotiating places to peer. We will discuss these next.

A. *Identifying Potential Peers: Affinity Test*

Peering between two providers A and B is beneficial when there are areas where only one has coverage. Such regions present an opportunity to collaborate and help to improve QoS for each others' customers. However, the presence of these areas should be symmetrical, i.e., the place where only A has coverage should be similar to the area size where only B has coverage. If that is not the case, there can be an imbalance in the potential benefits of a peering agreement, and therefore it will not be a stable relationship. We define α_A to be the area covered by A but not B, α_B to be the area covered by B but not A, and $\alpha_{A\cap B}$ to be the area covered by both A and B as shown in Fig. 2. If these two providers peer, we formulate the percentage increase in the coverage areas of A and B as follows:

$$\psi_A = 100\frac{\alpha_B}{\alpha_{A\cap B} + \alpha_A} \qquad \psi_B = 100\frac{\alpha_A}{\alpha_{A\cap B} + \alpha_B}. \tag{1}$$

If ψ_A and ψ_B are non-zero numbers, it shows potential for a peering relationship. If either one of the two is zero, it indicates a peering agreement may not benefit both providers. We refer to ψ_A and ψ_B as the provider's respective *affinity scores*. If two providers have non-zero *affinity scores*, it shows the potential of peering as there exist some areas where only one of them has coverage.

B. *Identifying Potential Areas for Peering*

A high-affinity score between two providers does not necessarily translate to a stable and mutually beneficial peering relationship. The peering providers need to negotiate and decide which areas and BSs will be the places where they will serve each others' users. We take a probabilistic approach to avoid potential congestion and limit peering to areas where traffic overload is unlikely. Since usage patterns are not publicly known, we merge county-level (a political subdivision of the states in the US) population and BS location data to estimate BS capacity and load. A detailed discussion can be found about the data and methods used in §V. BSs in densely populated areas are expected to handle many users and can therefore be unavailable for peering due to overloading. On the other hand, BSs in regions with low populations can be under-utilized because of a few connected users. Therefore, they can be considered available for peering as they will have enough capacity to handle more users. In the absence of real-world traffic, these approximations can be used to select areas where peering will be viable and not result in over-loaded BSs. This paper focuses on formalizing the problem of choosing the best peering areas and offering heuristics to solve it.

IV. Wireless Peering: A Simplified Formal Model

A. *Customer Satisfaction*

The *American Customer Satisfaction Index* lists key aspects that contribute towards customer experience in the context of a cellular network. We select the ones correlating to our proposed peering model and define CSAT as these elements function. CSAT gives an approximation of a customer's overall network experience in the *pre-connection*, e.g., service availability, and the *post-connection* phase, e.g., Internet speed.

1) Network Coverage: We use BS locations to approximate *county* network coverage area as percentage of its total area. Using county area as reference allows us to localize the effect of network coverage on customer satisfaction. We normalize network coverage in a specific county i to 0 and 1:

$$C_{ij} = \frac{\alpha_{ji}}{T[i]}, \quad i \in \mathcal{T}, j \in \mathcal{P}, \tag{2}$$

where $\mathcal{P}$ is the set of providers, $\mathcal{T}$ is the set of counties, α_{ji} is the network coverage area in square kilometers of provider j in county i, and $T[i]$ is the total area of county i.

2) Signal Quality: Signal strength depends directly on line-of-sight (LOS) distance between the BS and the receiver. For simplicity, we ignore other factors affecting signal strength and define the it using the inverse square law:

$$Q_k = \frac{1}{r_k^2}, \quad k \in \mathcal{K} \tag{3}$$

where $\mathcal{K}$ is the set of customers and r_k is the LOS unit distance between customer k and the closest BS. Q_k is normalized between 0 and 1.

3) Speed: If a large number of cellular devices are connected to the same BS, customers are expected to experience reduced transfer rates. We assess consumer satisfaction specifically with access speed by comparing provider-advertised expected upload/download rates to the actual speed. We define the network speed score S_k for customer $k \in \mathcal{C}$ as:

$$S_k = \begin{cases} \frac{D_k}{\hat{D}_k}, & D_k \leq \hat{D}_k \\ 1, & D_k > \hat{D}_k \end{cases} \tag{4}$$

where D_k is the actual data transfer speed that the customer experiences and $\hat{D}_k$ is the provider advertised speed. Assuming that all connected users consume a similar bandwidth on average, data transfer speed attenuates with each new connection added in excess of the BS load capacity. D_k can be defined as a function of the number of active connections:

$$D_k = \begin{cases} \hat{D}_k(1 - \Lambda^{\bar{u} - u^\circ}), & \bar{u} > u^\circ \\ D_k, & \bar{u} <= u^\circ \end{cases} \tag{5}$$

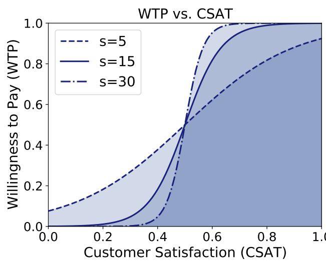


Fig. 3: S-shaped curve [21].

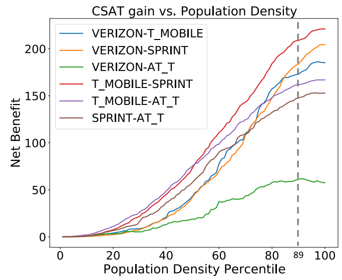


Fig. 4: Peering in counties

where Λ is the deterioration rate in (0,1), $\bar{u}$ is the total number of active BS connections, and u° is the BS load capacity in terms of the number of active connections it can handle without any reduction in individual bandwidth.

4) CSAT: We take the geometric mean of the three components to define the CSAT which is normalized between 0 and 1. The CSAT for provider j's customer k in county i is:

$$\sigma_{kij} = \sqrt[3]{C_{ij} Q_{ki} S_{ki}} \tag{6}$$

where $Q_{ki} = \frac{1}{|J_{ki}|} \sum_{u \in J_{ki}} Q_{kiu}$, $S_{ki} = \frac{1}{|J_{ki}|} \sum_{u \in J_{ki}} S_{kiu}$, and J_{ki} is the set of all positions customer k has been to in county i. Since we are using a geometric mean, if any one of the three matrices equals 0, the entire satisfaction score becomes 0. It also allows us to accurately capture the law of diminishing marginal returns, which in this context means that after some optimal level of QoS is achieved, improving QoS further will result in smaller increases in customer satisfaction. CSAT for provider j's network can then be calculated as the average CSAT of all of its customers, i.e.:

$$\sigma_j = \frac{1}{|\mathcal{K}_j|} \sum_{k \in \mathcal{K}_j} \frac{1}{|\mathcal{T}|} \sum_{i \in \mathcal{T}} \sigma_{kji} \tag{7}$$

where $\mathcal{K}_j$ is the set of customers of provider j.

B. Providers' Revenue

We outline CSAT's relation to customers' Willingness To Pay (WTP) and develop an economic model for the providers' revenue.

1) Willingness to Pay: Homburg *et al.* [21] use the *Prospect Theory* to present a functional structure to describe the relation between CSAT and WTP. If CSAT increases, customers are willing to pay more. Fig. 3 shows the S-shaped curve that represents empirical data collected from a research study conducted in the context of a restaurant. Assuming the cellular market follows a similar trend, we capture the effect of CSAT on WTP in the following equation:

$$w_{kj} = \frac{1}{1 + e^{-s(\sigma_{kj} - t)}} \tag{8}$$

where s and t are constants to normalize the values between 0 and 1, and σ_{kj} is the customer k's CSAT using provider j's service, which is a weighted average of σ_{kji}'s according to how much time the customer spends in each county i. The sensitivity constant, s, defines the steepness of the slope for the relation between customers satisfaction and their WTP. The higher s, the steeper the slope is, which means that a customer is susceptible to changes in QoS and vice versa. t represents a customer's expectation regarding QoS. A higher t shifts the curve to the right, suggesting that the customer is willing to pay if QoS is above a certain level. For the scope of this paper, we assume that the WTP-CSAT relation is symmetrical, i.e., $w_{kj} = 0.5$ at $\sigma_{kj} = 0.5$. The WTP-CSAT relation is normalized between 0 and 1 such that $w_{kj} \to 1$ as $\sigma_{kj} \to 1$ and $w_{kj} \to 0$ as $\sigma_{kj} \to 0$, we tune s in (8). Fig. 3 shows how different s values affect the WTP–CSAT relation.

2) Pricing: Users' Utility and Demand: The customer has no control over the price; however, a rational customer's reaction to price change directly affects it. Demand-Supply curve [22] represents this phenomenon. As the price of a product rises, customers' willingness to buy, more commonly known as the *demand*, falls. We utilize the concept of *Utility* and *Law of Diminishing Marginal Utility* as discussed earlier in Section IV-A4 to model a customer's behavior with regards to demand. Therefore, a rational consumer k subscribed to provider j should choose the quantity that maximizes his net utility (or surplus) which we define as:

$$U(x) - f_j x, \tag{9}$$

where $U(x)$ is the customer utility that results from consuming x amount of the product and f_j is the unit price that the customer has to pay the provider j. For customer k, we define the utility function as $U_k(x) = w_k \cdot \log(x), \;\; w_k > 0$ where w_k is the WTP of customer k, which is constant that allows us to give the utility function a dollar value that is comparable to the product price. x is the quantity of product consumed, e.g., the amount of wireless data and/or the number of cellular calls. We derive (9) with respect to quantity (x) and equate it to zero to calculate the maximum net utility. It yields the well-known optimal demand and price equilibrium of $0 = U_k'(x) - f_j$, i.e., $0 = \frac{w_k}{x} - f_j$. The relation between price and quantity demanded can the be derived as

$$x_j(f) = \frac{w_k}{f} \tag{10}$$

Assume WTP, w_k, increases because of an increase in customer satisfaction. Then, as explained in §IV-B1, the demand function proves that the resultant curve will shift rightwards. Since peering requires no additional costs, this increase in the price because of the demand shift contributes solely to an increase in profit.

3) Provider j's Total Revenue: Providers look to maximize revenue and profit. We define the total revenue of provider j as follows: $R_j = f_j \sum_{k \in \mathcal{K}} x_k(f_j)$ where f_j is the subscription fee charged to customers, (K) is the provider's customer set, and $x_k(f_j)$ is the demand function for customer k.

The number of users a provider can handle is upper bounded by its capacity. Ideally, the demand should equal this capacity. If it is lower, the provider may reduce the price to increase demand. If it is higher, increasing the price can reduce the demand to the desired level. Therefore, the provider needs to find the optimum price, which we denote as f^*, to maximize the total revenue R.

Using §IV-B2-defined demand function, and assuming the provider's eagerness to match the demand and capacity, the optimum price can be determined as follows:

$$\sum_{k\in\mathcal{K}} x_k(f^*) = c \tag{11}$$

$$f^* = \sum_{k\in\mathcal{K}} \frac{w_k}{c} \tag{12}$$

where c is the capacity and w_k is the WTP for customer k. We see f^* depends on the users' WTP. We have already shown that peering can raise user WTP by increasing CSAT. Therefore, we can conclude that peering allows providers to improve end-user QoS and increases the optimum fee, f^*. Relating this change in subscription fee to the revenue function presented in §III shows that the total provider revenue increases. Since this comes at no additional cost, the change contributes to the profit directly:

$$R_j = K_j f_j^* \tag{13}$$

$$R_j = K_j \sum_{k\in\mathcal{K}} \frac{w_k}{c} \tag{14}$$

where K_j is the number of subscribers for provider j.

C. Peering Optimization

Peering candidate and location selection can be defined as an optimization problem for two providers A and B. As part of the peering contract, providers need to select peering locations (counties) to maximize net monetary benefit and increase in average CSAT for both providers. Since it is a negotiation process between two providers, it is possible that while one county offers great potential to provider B, it is not a good enough peering location for A. Because of this difference in perspective and that peering is a two-way relationship, choosing all counties with a net positive CSAT change may not always be the optimal solution.

Let OPTIMALPEERING$(\mathcal{T}, \Delta\sigma_A, \Delta\sigma_B)$ denote the peering optimization problem, where $\mathcal{T}$ is the set of counties, and $\Delta\sigma_A$ and $\Delta\sigma_B$ are the vectors of CSAT gain for providers A and B. We write OPTIMALPEERING as follows:

$$\max_{\mathcal{T}^*\subseteq\mathcal{T}} \left(\sum_{i\in\mathcal{T}^*} \Delta\sigma_{Ai}\right)\left(\sum_{i\in\mathcal{T}^*} \Delta\sigma_{Bi}\right) \tag{15}$$

$$\text{s.t. } \Delta R_A, \Delta R_B \geq 0 \tag{16}$$

$$\sum_{i\in\mathcal{T}^*} \Delta\sigma_{Ai} \geq 0, \quad \sum_{i\in\mathcal{T}^*} \Delta\sigma_{Bi} \geq 0 \;\; \forall i \in \mathcal{T} \tag{17}$$

Since the CSAT values, $\Delta\sigma_{Ai}$ and $\Delta\sigma_{Bi}$, are in [-1,1], the maximum possible value of the objective function in (15) will be N^2 where $N = |\mathcal{T}|$. In this case, all counties are selected for peering and each provider obtains 100% increase in its CSAT. Since peering benefit is dependent on each other's service quality, the goal for selecting the peering counties $\mathcal{T}^*$ is to maximize the collective benefit for both providers, which is the product of the CSAT gains. Thus, the objective function in (15) maximizes the product of the total CSAT benefit of the both providers. This is a crucial dynamic since the closer the individual benefits of the two providers, the stronger the peering relationship will be (16) and (17), respectively, assuring no provider looses revenue and has a positive CSAT gain summed over all selected counties $\mathcal{T}^*$.

The complexity of OPTIMALPEERING is based on the number of counties N. A search for the best subset of counties, $\mathcal{T}^*$, will involve a running time of $\mathcal{O}(2^N)$, as there are 2^N subsets of counties. For small N, this may be possible. However, N can be quite large, and further, the problem can be solved at finer granularity, e.g., peering locations can be selected at each cell site instead of county. We show that OPTIMALPEERING is NP-hard and present two heuristics.

Algorithm 1 Reduction to Subset Sum

Inputs: $\mathcal{T}$, $\Delta\sigma_A$, $\Delta\sigma_B$
Output: Set of counties $\mathcal{T}^*$
$N \leftarrow |\mathcal{T}|$
$\Delta\sigma_{max} \leftarrow 100$
for $x \leftarrow 1:N$ **do**
  for $y \leftarrow 1:N$ **do**
    $\mathcal{L} \leftarrow \Delta\sigma_{Ax}.\Delta\sigma_{By}$
  end for
end for
$U \leftarrow N^2(\Delta\sigma_{max})^2$
while $U > 0$ **do**
  $L^* \leftarrow$SUBSETSUM$(\mathcal{L}, U)$
  $\mathcal{T}^* \leftarrow \emptyset$
  for $x \leftarrow 1:N$ **do**
    if $\Delta\sigma_{Ax}.\Delta\sigma_{Bx} \in L^*$ **then**
      $\mathcal{T}^* \leftarrow \mathcal{T}^* \cup x$
    end if
  end for
  for $x \leftarrow \mathcal{T}^*$ **do**
    for $y \leftarrow \mathcal{T}^*$ **do**
      if $\Delta\sigma_{Ax}.\Delta\sigma_{By} \notin L^*$ **then**
        Go to DECR
      end if
    end for
  end for
  DECR: $U \leftarrow (U-1)$
end while
return $\mathcal{L}^*$

1) NP-Hardness: We show that OPTIMALPEERING is NP-hard by reducing it to Subset Sum, which is one of the NP-complete problems [23]. Assume that a procedure solves the SUBSETSUM$(\mathcal{L}, U)$ where $\mathcal{L}$ is a set of integers and U is a target value, and it returns the subset of $\mathcal{L}$ that sums to U.

We consider a quantized version of OPTIMALPEERING where $\Delta\sigma_A$ and $\Delta\sigma_B$ can only be integers. In particular, we assume σ values are scaled from [0,1] to [0,100] and rounded to closest integer, i.e., $\sigma_{Ai} \leftarrow \lfloor 100\sigma_{Ai} \rceil$ and $\sigma_{Bi} \leftarrow \lfloor 100\sigma_{Bi} \rceil$, from their calculation in (7).

We reduce OPTIMALPEERING$(\mathcal{T}, \Delta\sigma_A, \Delta\sigma_B)$ to SUBSETSUM$(\mathcal{L}, U)$ in Algo. 1. It calls SUBSETSUM with the highest possible U and then decrements it until there is a solution. The key parameter here is $\Delta\sigma_{max}$ which is set to 100 as the maximum amount of CSAT gain can be 100 after the quantization. Given this, the highest possible objective value in (15) can be $N^2(\Delta\sigma_{max})^2$, where U is initialized to. The algorithm sets up a vector N^2 integers that are pairwise multiplications of $\Delta\sigma_A$ and $\Delta\sigma_B$. Then, the algorithm inspects the returned solution L^* from SUBSETSUM. Two conditions must satisfy in order for the solution to be valid for OPTIMALPEERING: (1) If a county x is selected, the product of the CSAT gains of A and B for x must be in the solution. (2) For all selected counties, all pairwise products of the CSAT gains of A and B on those counties must be in the solution. In the first for loop inside the while loop, the algorithm inspects the integers selected by SUBSETSUM and composes the list of selected counties. In the next nested for loop, it checks whether all pairwise products of CSAT gains on those selected counties are included.

Finally, as another requirement for NP-hardness proof, the reduction algorithm runs in polynomial time. In particular, the complexity of the algorithm is $\mathcal{O}(N^5 * (\Delta\sigma_{max})^2)$, since the while loop runs $N^2 * (\Delta\sigma_{max})^2$ times and each iteration takes $\mathcal{O}(N^3)$ time due to the for loops.

D. Heuristic Approaches

Since finding the optimal selection of counties is NP-hard, we employ two heuristic approaches that allow us to make an informed county selection for peering.

1) Population Density Threshold: Congestion directly relates to population; we avoid densely or moderately populated areas and choose counties for peering with population density below a particular threshold value. Fig. 4 shows the providers' net benefit with increasing threshold. Most of the counties in Texas are sparsely populated, making them feasible for peering. If the threshold is too high after a certain point, peering is not as beneficial and, in some cases, can hurt CSAT.

We find the population density threshold for each peering contract beyond which the benefit from peering remains negligible (under 1%). The lowest of these values is 89th percentile, for Verizon-AT&T. Taking a conservative approach, we consider this the optimal threshold for county selection, which is 235 persons per km^2 for Texas. Finally, we assess the performance of the heuristic in later sections.

Algorithm 2 County Selection: Sorted Sum

Inputs: $\bar{\mathcal{T}}$, $\Delta\sigma_A$, $\Delta\sigma_B$
Output: Set of counties $\mathcal{T}^*$
$\mathcal{T}^* = \{\}$
function SORTEDSUM($\bar{\mathcal{T}}$,$\Delta\sigma_A$, $\Delta\sigma_B$)
    $n \leftarrow |\bar{\mathcal{T}}|$
    if $n = 1$ **then**
        return $[\max(0, \Delta\sigma_{Ai}), \max(0, \Delta\sigma_{Bi})]$
    end if
    $[sumA, sumB] \leftarrow$ SORTEDSUM$(\bar{\mathcal{T}}[0 : n-1], \Delta\sigma_A, \Delta\sigma_B)$
    if selecting i increases net gain **then**
        $\mathcal{T}^*$.insert($i \in \bar{\mathcal{T}}$)
        return $[sumA$+$\Delta\sigma_{Ai}$, $sumB$+$\Delta\sigma_{Bi}]$
    else
        return $[sumA, sumB]$
    end if
end function
Reverse Sort $\bar{\mathcal{T}}$ by $\Delta\sigma_{Ai}\Delta\sigma_{Bi}$
SORTEDSUM$(\bar{\mathcal{T}}, \Delta\sigma_A, \Delta\sigma_B)$
return $\mathcal{T}^*$

2) Sorted Sum: Given $\Delta\sigma_{ji}$ and $\Delta\sigma_{j'i}$ for providers j and j' in all counties $i \in \mathcal{T}$, we discard counties if both providers are losing in terms of CSAT ($\Delta\sigma_{ji} < 0$ and $\Delta\sigma_{j'i} < 0$). The rest of the values are sorted in reverse order of $\Delta\sigma_{ji}\Delta\sigma_{j'i}$ which we refer to as $\bar{\mathcal{T}}$. This allows us to give the highest preference to counties where both providers are gaining at a similar level, and the less preference to counties where one of the providers is gaining less than the other. To select $\mathcal{T}^*$, we use a recursive solution as shown in Algo. 2 that ensures maximum net benefit (15) in the given order of counties. Starting from the last county $n \in \bar{\mathcal{T}}$, we select it if it increases the net benefit, i.e.,

$$\left(\sum_{i\in\bar{\mathcal{T}}}^{n} \Delta\sigma_{ji}\right)\left(\sum_{i\in\bar{\mathcal{T}}}^{n} \Delta\sigma_{j'i}\right) > \left(\sum_{i\in\bar{\mathcal{T}}}^{n-1} \Delta\sigma_{ji}\right)\left(\sum_{i\in\bar{\mathcal{T}}}^{n-1} \Delta\sigma_{j'i}\right) \tag{18}$$

where $\sum_{i\in\bar{\mathcal{T}}}^{n-1} \Delta\sigma_{ji}$ is calculated recursively. Since the list is sorted, we are able to get $\mathcal{T}^*$ in linear time complexity. While this heuristic-based selection does not give the global maximum net benefit, it performs much better than the population density threshold heuristic.

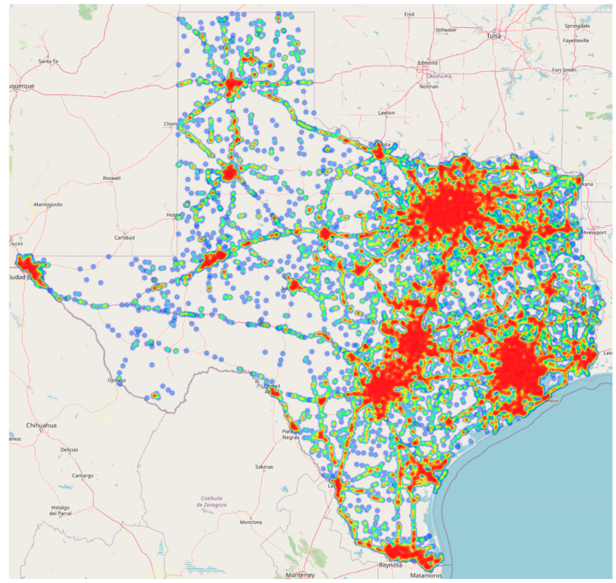


Fig. 5: BS Location heat map for AT&T in Texas.

V. SIMULATION AND ANALYSIS

We employ a systematic and practical approach to evaluating the role and impact of peering in wireless networks. We design and develop a simulator that mimics the real-world wireless network and allows us to characterize the *modus operandi* of cellular networks. Besides, it helps us study the relation between peering, end-user QoS, and its effect on the provider's net earnings.

A. Data Set

We used several data-sets for the evaluation setup:

OpenCellID: It is the largest crowd-sourced data-set for BS locations [24]. Cellular signal data is collected using mobile application installed by volunteers. This raw data is then used to map BS locations.

Networks and Subscriptions: The OpenCellID data does not provide information regarding which provider each BS

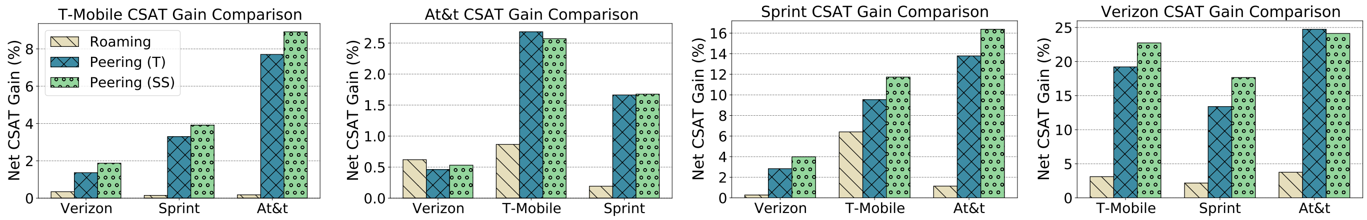


Fig. 6: Peering outperforms Roaming w.r.t. revenue gain in both heuristics.

TABLE III: BS radio types

	Speed (Mb/s)	Range (km)		Speed (Mb/s)	Range (km)
LTE	20.0	3.2	**CDMA**	5.0	6.4
UMTS	2.5	4.8	**GSM**	0.5	16

belongs to. However, it does include Mobile Country Code (MCC) and Mobile Network Code (MNC) for each BS. We use public networks and subscriptions [25] to identify the provider for each of the BS in the OpenCellID data.

State and County Boundaries: We identified the State and County each BS is located in using the US Cartographic Boundary from the Census Bureau's TIGER database and the BS latitude/longitude values [26], [27].

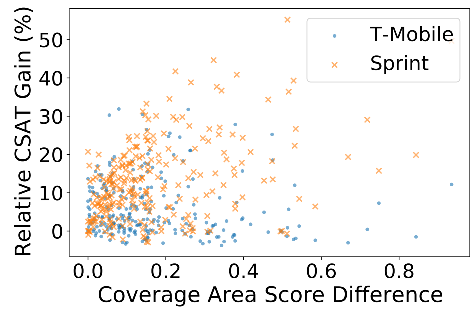
State and County Population: To estimate customer presence, we used the US CENSUS data that provides State and County level population data [28].

We design a virtual cellular network consisting of BSs and mobile users. Using the data sets discussed above, we ensure that their numbers, locations, and properties are as close to reality as possible. Thus, the simulated BSs accurately represent the real-world BSs, and the simulated users accurately represent the real-world users. Fig. 5 shows a geographical heat map that we drew using the BS location data for AT&T in Texas. It is seen that the BS density is particularly high in major cities. Also, it should be noted that these maps are not representative of the provider coverage as that varies with each type of BS.

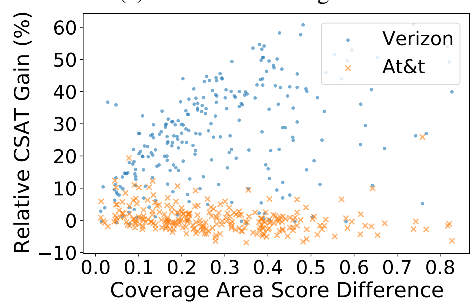
We believe this simulator can be used for different experiments in this area of research. Therefore, we have made its source code and the compiled data set publicly available[2]. The performance of different pricing or spectrum sharing models can be tested using the same underlying network. In addition, making the code publicly available will allow researchers to contribute to this tool and improve its accuracy and efficiency.

In this paper, we limit the extent of our experimentation using this simulator to only Texas, the second largest and the second most populated state in the US. It also has the highest number of counties (254). Since the majority of our analysis is county specific, Texas provides the most diverse range of densely and sparsely populated counties, allowing us to test our model in a variety of different scenarios, representing the majority of the rest of the US.

[2]https://github.com/shahzebmustafa/Wireless-Peering-Simulator



(a) Balanced CSAT gain.



(b) Imbalanced CSAT gain.

Fig. 7: CSAT gain Comparison in each county.

B. Simulation

1) Providers & Customers: We combine the data from OpenCellID and the MCCs, MNCs as discussed in Section V-A. We use GeoJSON-generated data to determine in which county each BS is located. GeoJSON data allows us to generate polygons with the exact dimensions for each of the county boundaries and calculate the county coverage area for each provider (*which is upper bounded by its geographical area*) as $\alpha_{ji} = \bigcup_{b=0}^{n_{ji}} \pi \bar{r}_b^2$, where n_{ji} is the total number of BSs in county i for provider j, and $\bar{r}_b$ is BS b's maximum signal range. We calculate the total provider coverage area with the following assumptions about the BS: (1) BS $\bar{r}_b$ depends on the radio type, Table III; (2) All BSs have at least three antennas, hence the total area that a BS covers will always be sphere; and (3) No interference among the BSs themselves.

We generate users with random locations and movements by employing the following constraints to make user interaction with our virtual network more realistic: (1) The number of users in a county is directly proportional to its local population;

(2) The number of users of a provider is directly proportional to its BS count in a county; (3) The user mostly remain within the county that they belong to, and therefore are most concerned by their local cellular Quality-of-Service (QoS).

2) Measurement: We initialize our simulation by generating a programmable county map of Texas with BSs and users. While the BSs are positioned on pre-computed coordinates from OpenCellID, user locations are selected at random within their respective counties. We scale down the actual population of each county and we generate $\frac{1}{1,000}\rho_i$ resident users where ρ_i is the population for county i. These users are then divided into four groups proportional to the number BSs, one for each provider. We set the maximum data transfer speed of each BS based on its radio type from Table III, provided in OpenCellID data. To account for the scaled-down number of customers, we also scale down a BS's load capacity u° to only one per BS. The data transfer rate sees an exponential decay with each added connection to the BS. While the rate of this decay depends on various factors, for this simulation, we use it as 0.05, i.e., 5% reduction in speed of all connected users for every new connection. User movements are probabilistically restricted within their local county, i.e., a user's next (randomly selected) location is in their local county with 90% probability.

The movement to other counties is analogous to a trip for 1 – 10 iterations. Every time user location is updated, User Equipment (UE) sends connection requests to all BSs within their range. In doing so, preference is given to the user's primary provider's BS. If other BSs offer a significantly better signal quality, which we measure using LoS distance, then connection requests are sent to them also. This request is not accepted in the absence of a roaming or peering contract, in which case UE sends a connection request to increase LoS distance. Once a BS accepts the connection request, we calculate the signal strength, Q_k, coverage area score, C_{ij}, and the speed score, S_k. The speed score is the ratio of the actual speed, which depends on BS load, to the expected speed, which depends on the radio type from Table III. Coverage area score is the ratio of the coverage area in county i for provider j, which is calculated as described earlier in Section V-B1, to the county area. Similarly, signal strength is calculated as shown in (3) using LoS distance r from the BS. We use these measurements to calculate the average CSAT score for each user over 100 simulation iterations.

C. Results

1) Peering in Individual County: We observe the peering model in each county individually and take measurements to record user CSATs at each location until it converges to a stable value. We perform it for all counties as part of a two-staged measurement study. In the first stage, we calculate average county CSATs for each provider, assuming none have any peering or roaming agreement. We use the same measurement techniques in the second stage with a bilateral peering agreement at all locations. We run six simulations for all possible peering combinations among four providers and compare the average CSAT values from the two stages. Fig. 7 summarizes the findings for two peering contracts: T–Mobile with Sprint and Verizon with AT&T.

2) Impact of Coverage Area: For each peering contract, we calculate the CSAT gain $\Delta\sigma$ for all counties, indicating the change in average provider CSAT score due to peering. Since this change is different for each provider, it is possible that only one of the providers can benefit from a peering relation in the given county. To design a county selection criteria, we analyze the relation between $\Delta\sigma$ and the difference in county coverage between the two providers. We use the percentage change in provider CSAT *relative* to its score. The intuition behind this method is that for a provider, improving the CSAT score becomes more complex as it moves closer to 1. It happens because of the diminishing nature of the CSAT function. Therefore, we calculate the relative CSAT gain as a percentage of $1 - \sigma$ where σ_{ji} is provider j's CSAT score in county i without peering.

Fig. 7a and Fig. 7b illustrate the relation between CSAT gains and differences in the coverage scores $\mathcal{C}_{ji}$ between the provider j (requester) and j' (candidate) in county i. As the difference between network coverage increases, CSAT gain also increases at a different rate for both providers. If the difference is high, providers with the lower average CSAT are expected to benefit more from a peering contract. If the difference between $\Delta\sigma$ increases with moving further along the x-axis, it becomes more like a customer-provider relationship rather than a collaborative one. As the coverage difference reduces, both providers have a similar QoS in those locations and hence more potential for peering. Since Sprint and T-Mobile are identical in size, they both can benefit from peering. However, in the case of AT&T and Verizon, peering is largely beneficial only for Verizon.

At&t has the best service in Texas in all aspects: coverage area, data speed and signal quality. With no coverage in 45 counties, Verizon scores the lowest on our scale. The results reported in Figure 7 show that bilateral peering is more beneficial for the provider with worse coverage. Compared to Verizon, At&t has a much better QoS in most of the counties, which is why Verizon doesn't have much to offer with peering. However, since T-Mobile and Sprint both have comparable cellular coverage, peering is mutually beneficial for both of them. We choose these two pairs specifically to illustrate how the effectiveness of peering is highly dependent on how comparable in size the two providers are.

3) Peering vs. Revenue Gain: We execute a two-stage experiment for the entire state instead of a single county. As described in Section V-B2, users can travel to other counties; some part of their CSAT score now also depends on the QoS in other counties that they visit. We use proposed heuristic county selection procedure from Section IV-D to get $\mathcal{T}^*$. We enable peering in all counties in $\mathcal{T}^*$ and simulate ≈30,000 customers. In both stages, we collect the average CSAT scores as reported in Figure 6. The bar charts show the change in average CSAT for each provider, and peering always yields better results when compared to roaming. The performance of both heuristics, T and SS, remains similar, although SS does tend to perform better in more cases.

We use (14) with c = 100 to calculate the change in price primarily caused by this increase in CSAT. For different values of the consumer sensitivity constant s, we observe the gain in revenue each provider can expect with wireless peering. When the sensitivity is too low, wireless spectrum market moves towards a commodity market, and there is no benefit to use wireless peering. When the sensitivity is too high, the customers are content with paying higher fees for even a slightly better QoS. Both of these scenarios are highly unlikely to occur since the wireless spectrum is a scarce resource and not probable to become a commodity without any major breakthrough. Furthermore, it is implausible that the wireless spectrum becomes so scarce as to make it a luxury. It is fair to assume that as long as the demand is sufficient, providers will continue striving to make the spectrum market more efficient.

VI. Summary and Discussion

Despite significant developments in wireless networks, County-wide cellular service in the US remains unreliable at large. In addition, the mobility of cellular users makes the mass deployment of new technology particularly difficult. *wireless peering* aims to act as a trustworthy model that cellular providers can use to collaborate. We tested wireless peering on a virtual cellular network and our experimental results show great potential in terms of cellular service and provider revenue. In addition, T-Mobile and Sprint have officially merged, reaffirming our simulation results as they offer the highest potential in terms of revenue gain and QoS improvement.

We have identified various limitations of wireless peering, including free-riding and the lack of publicly available accurate cellular and user mobility data. No government approved or official data set for accurate GPS positioning and configuration for BSs is publicly available. The data provided by the Federal Communications Commission is incomplete. It only contains position data for registered cell towers and BSs. Quite often this registration is associated with a third party management entity, which means that a specific carrier's cell towers can rarely be identified using this data. In addition to that, not all BSs (specifically micro BSs) need to be registered with a central authority. Nevertheless, we were able to design a solid theoretical and empirical model for wireless peering. We aim to improve the county or BS selection for peering by employing stronger heuristics and experimenting with dynamic selection models, that make decisions based on live traffic patterns. We believe that despite several limitations in this prefatory design, *wireless peering* has the potential to become a reality and be deployed worldwide.

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