

# Magus: Minimizing Cellular Service Disruption during Network Upgrades

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## ABSTRACT

Planned upgrades in cellular networks occur every day, may often need to be performed on weekdays, and can potentially degrade service for customers. In this paper, we explore the problem of tuning network configurations in order to mitigate any potential impact due to a planned upgrade which takes the base station off-air. The objective is to recover the loss in service performance or coverage which would have occurred without any modifications. To our knowledge, impact mitigation for planned base station downtimes has not been explored before in the literature. The primary contribution of this work is a *proactive* approach based on a predictive model that uses operational data of user density distributions and path loss (rather than idealized analytical models of these) to quickly estimate the best power and tilt configuration of neighboring base stations that enables high recovery. A secondary contribution is an approach to minimize synchronized handovers. These ideas, embodied in a capability called Magus, enables us to recover up to 76% of the potential performance loss due to planned upgrades in some cases for a large US mobile network, and this recovery varies as a function of base station density. Moreover, Magus is able to reduce synchronized handovers by a factor of 8.

## CCS Concepts

•**Networks** → *Wireless access points, base stations and infrastructure; Network performance modeling; Network management; Wireless access networks;*

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## Keywords

Cellular Network; Performance Modeling; Network Reconfiguration

## 1. INTRODUCTION

Mobile users increasingly rely upon cellular networks for their daily activities such as Web browsing, voice communication, video on demand, social network applications, and business critical tasks. As such, disruption of cellular service is not received well by customers: service outages are often publicly reported in mainstream media outlets and some studies report the impact of these kinds of service disruptions to be in the billions of dollars [8].

One reason for service disruption is due to some types of planned network upgrades. Cellular service providers are rolling out new features (e.g., Voice over LTE) and upgrades at a rapid pace to keep up with growing traffic and application demands, and to provide ultra-high quality of service and reliability. Network upgrades can involve new software releases, hardware updates, configuration changes and even equipment re-homes.

These planned upgrades have the potential to impact cellular service performance and thus have to be carefully planned and executed. Some upgrades in the radio access network require the cellular base station to be taken off-air for the duration of the planned work. For example, during power plant work or hardware replacement, the cellular base station is not available to provide service to the end-users. The cellular network operators carefully plan such upgrades during the off-peak hours and low-impact days, when possible.

Despite the extraordinary care in scheduling these upgrades, it is sometimes not possible to avoid service disruptions. Sometimes, upgrades can take longer than expected and thus spill over into the busy hours. In other cases, they may have to be conducted during business hours depending on vendor availability. Moreover, for certain locations such as busy airports, there is no specific preferred time for scheduling the upgrade because of the 24/7 usage at these locations.

In this paper, we focus on planned upgrades that occur during the business hours and require the base station to be

taken offline for the duration of the work. Such planned upgrades are not infrequent. To quantify this, we obtained one year’s worth of data on planned upgrades from a large cellular network in North America. We observe that planned upgrades occur every day of the year and they are more than twice as likely to occur on Tuesdays through Fridays than on other days. Typically, these planned upgrades last 4-6 hours and impact all radio access technologies (such as LTE, UMTS as well as GSM). For some planned upgrades, service disruptions cannot be completely avoided. Depending on the radio network coverage and capacity, some end-users might either be denied service (due to coverage holes), or have a degraded service performance (due to overload conditions).

**Our approach.** We focus on the important problem of minimizing service disruption during network upgrades. Our work relies on the following observation. When a base station is taken off-air, end-users can re-attach to neighboring base stations depending on their coverage overlaps and resource availability. In general, radio network planners attempt to maximize coverage and minimize interference by setting base station configuration parameters such as transmit power and antenna tilt. However, if a base station goes offline during an upgrade, the coverage and capacity in that group of base stations will become sub-optimal, and it may be possible to share resources from neighboring base stations. Thus, there is an opportunity to improve the end-users’ quality of experience during an upgrade by controlling the configuration (e.g., increasing the transmit power, or adjusting the antenna tilt) on neighboring base stations.

Today, many cellular networks do not perform this kind of adaptation. Some advanced systems have deployed dynamic reconfiguration techniques which iteratively and dynamically adjust the configuration parameters of neighboring base stations to converge to near-optimal coverage and capacity if there is any kind of base station outage (not just ones caused by planned upgrades). As we discuss later, this dynamic adaptation in these “self-organizing networks” [18] can take significant time because each step of the iteration requires base stations to measure signal and interference parameters to drive the adaptation. Further, there can be operational constraints on the number of configuration changes that can be pushed to a production network.

Given the prevalence and impact of planned upgrades, we propose a new approach, called Magus, for automatic network re-configuration to minimize service disruptions during planned upgrades. Before the base station is taken off-air for planned work, Magus *proactively migrates end-users away towards its neighbors by tuning the configuration accordingly*. This helps by partially *recovering* the degradation in performance or coverage resulting from the upgrade.

There are several challenges in achieving this kind of proactive re-configuration. First, determining the best new configuration for the neighboring base stations can be challenging, especially in dense urban settings. This is because modern base stations have a large number of power, tilt, and other configuration settings, an offline base station may have tens of neighbors or more in an urban area, and changing the con-

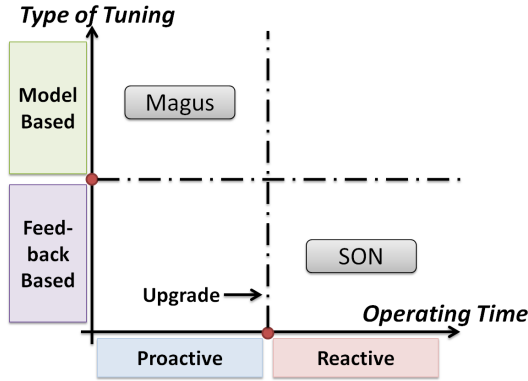
figuration of one base station may increase interference for users attached to other neighboring base stations. Moreover, the impact of a configuration change may not be known a priori, since it depends upon a large number of complex factors including terrain, weather, the number of users etc. Second, the migration of end-users involves a re-attachment to the new base station and needs to be carefully managed. The re-attachment occurs via a handover and a handover is technology and implementation dependent. Moreover, synchronized handovers resulting from a sudden configuration change can severely strain the cellular network and potentially cause service disruptions for users.

To overcome the first challenge, Magus builds upon a **predictive model** to automatically learn a near-optimal configuration setting. This model can quickly evaluate the impact of configuration changes without deploying them. The model leverages the availability of large databases of path loss information that are often used for network planning purposes (but, to our knowledge, have not been proposed for dynamic re-configuration). Using this path loss information, Magus can estimate signal-to-interference ratios resulting from the configuration change, then estimate the potential impact on coverage or capacity, allowing it to quickly search the configurations space. To address the second challenge, Magus proactively starts migrating users to neighboring base stations (and carefully *tuning* their configurations while doing so) before the scheduled planned upgrade, so that the impact of synchronized handover is minimized, and most users are migrated before the planned upgrade.

In this paper, we present the design, implementation and evaluation of Magus in the context of LTE radio access technology on a single carrier. However, the principles underlying Magus apply to multiple carriers and other technologies as well, such as small cells and UMTS. We do not tackle re-configuration and migration of users across radio access technologies and defer it to future work.

**Our contributions.** The paper makes four contributions. First, a qualitative analysis (Section 2) of the solution space reveals the tradeoffs between proactive (before upgrade) and reactive (after upgrade) and between a model-based approach such as Magus and a feedback-based approach (which adapts configurations after taking measurements). Second, experiments from an LTE testbed (Section 3) illustrate the potential of re-configuring neighboring base stations in recovering lost performance. The third contribution is the design of Magus, a novel predictive model-based proactive re-configuration approach that relies on operational<sup>1</sup> data available to large mobile carriers (Section 4 and Section 5). Finally, evaluations using data from a large US mobile carrier on 3 major US cellular markets show that Magus can recover up to 76% of lost performance, and reduce synchronized handovers by a factor of 8. Interestingly, the performance recovery varies by area, being highest in suburban areas of moderate base station density; these areas predominate in the three markets. This variability is surprising because planners

<sup>1</sup>For operational data, we explicitly do not show any service performance numbers in the paper for proprietary reasons.



**Figure 1**—Two dimensional solution space: *operating time* can be either proactive or reactive; *type of tuning* can be either model-based or feedback-based.

do account for outages, and network planning is a mature field; our result opens up avenues for better network planning to enable higher recovery after planned upgrades.

## 2. THE SOLUTION SPACE

In this section, we qualitatively explore the solution space for minimizing service disruption during planned network upgrades. Before describing the solution space, we briefly introduce some terminology. We denote by  $\mathbb{C}$  the *configuration* of the cellular network at any given instant. Each base station can be configured using a number of parameters such as transmit power, antenna tilt, and so on, and  $\mathbb{C}$  represents the collective parameter settings of all base stations in the network. To *tune* a configuration means to change the values of parameters for (some of) the base stations in the network. Thus, tuning takes the network from some configuration  $\mathbb{C}_1$  to another configuration  $\mathbb{C}_2$ . Finally, each configuration is associated with a *utility*, which measures the goodness of the configuration. Typical utility functions capture either coverage criteria (i.e., increase the number of connections that would have otherwise being dropped), or service performance criteria such as data throughput, or combined coverage and service criteria. We make these notions more precise in the next section.

Abstractly, a network reconfiguration after a planned upgrade (indeed, after any network change) takes the network from one configuration  $\mathbb{C}_{before}$  to another  $\mathbb{C}_{after}$ . This is done by tuning the configurations, with the goal of arriving at a maximal utility configuration.

As illustrated in Figure 1, the solution space for network reconfiguration is defined by two dimensions: (i) the **operating time** for tuning the configuration either before the base station going off-air (*proactive*), or after (*reactive*), and (ii) the **type of tuning** which can either be *model-based*, or *feedback-based*.

A model-based approach estimates configuration parameters by leveraging traffic and performance history (e.g., how much traffic did the base station see at the same time the previous day or the previous week?), as well as a detailed

terrain-aware model of network path loss information<sup>2</sup>. When a base station goes down, the model-based approach directly tunes the neighbors to the optimal configuration.

On the other hand, a feedback-based approach iteratively tunes configurations, relying, at each iteration, on measured performance (the “feedback”) after the previous iteration. This performance feedback consists of measured coverage and capacity parameters, and accurately represents the traffic and service performance during the planned upgrade. The feedback-based approach terminates when it reaches a configuration whose performance cannot be improved.

A feedback-based approach can take  $K$  iterations to reach the optimal, whereas a model-based can reach optimal in 1 iteration. Depending on the number of neighbors and the possible values that the configuration parameters can take, the number of iteration  $K$  can be very large. On the other hand, if the network and traffic conditions do not match the history or the path loss model, then the model-based approach might reach a sub-optimal configuration with lower utility than a feedback-based configuration.

This suggests that a hybrid approach may perform well: we can use the model-based approach to reach a “good” but sub-optimal configuration  $\mathbb{C}_{so}$ , and a feedback-based approach to go from  $\mathbb{C}_{so}$  to a higher utility  $\mathbb{C}_{after}$  in a small number of steps, denoted by  $k$  and  $k \ll K$ . For the rest of the paper, when we discuss a model-based approach, we implicitly assume it is augmented with a feedback-based phase that corrects for deviations from the model or from traffic history.

Let  $\mathbb{C}_{before}$  be the configuration before an upgrade,  $\mathbb{C}_{upgrade}$  the configuration just after the base station is taken down, and  $\mathbb{C}_{after}$  as the configuration attained after tuning the neighbors. Let  $f(\mathbb{C}_{before})$ ,  $f(\mathbb{C}_{upgrade})$ , and  $f(\mathbb{C}_{after})$  respectively represent the utilities of these configurations. Then:

$$f(\mathbb{C}_{before}) > f(\mathbb{C}_{after}) \geq f(\mathbb{C}_{upgrade})$$

With no tuning of neighbor configurations, the utility function would stay at  $f(\mathbb{C}_{upgrade})$  for the duration of the planned upgrade. However, the key observation in this paper is that there exist opportunities for improving the overall utility to reach  $f(\mathbb{C}_{after})$  by tuning the configurations. This discussion suggests four strategies.

**Reactive feedback-based.** Tuning starts after the base station is taken off-air and configurations are iteratively optimized using performance feedback until the utility function cannot be further improved or the algorithm reaches the maximum number of iterations permissible. Prior work on Self Organizing Networks [18] (SON) represents an instance of a reactive feedback-based approach, albeit for unplanned base station outages.

**Reactive model-based.** After the base station is taken off-air, this strategy takes one iteration to reach the optimal configuration setting on the neighbors. The advantage is faster convergence time to the final configuration, but the network may have a utility  $f(\mathbb{C}_{upgrade})$  just after the base station is taken down, and before the final configuration is reached.

<sup>2</sup>Such models (e.g., [7]) are often used for network planning.



**Proactive feedback-based.** This approach seeks to iteratively reach the optimal configuration setting before the base station goes down, using performance feedback. An example strategy would start reducing the transmission power of the target base station (that is going to be offline) and in each iteration, tune the configuration settings of the neighbors to achieve a maximum value for the utility function.

**Proactive model-based.** This strategy uses predictive techniques to automatically learn the optimal configuration setting for the neighbors before bringing down the base station.

Of these approaches, proactive model-based achieves the best performance by ensuring that the utility function never goes below the optimal  $f(\mathbb{C}_{after})$ , and it reaches the optimal configuration in  $1 + k$  step. The only disadvantage of the proactive model-based solution is the excessive number of handovers that would occur, at each step, from the base station under planned upgrade to its neighbors. We address this by proposing a new proactive model-based strategy, Magus, that makes gradual changes and reaches the optimal configuration. Note that only the model-based approach knows  $\mathbb{C}_{after}$  a-priori and can ensure that the utility function in each iteration never goes below this value.

### 3. BENEFITS OF RECONFIGURATION

In this section, we illustrate the potential of adaptively tuning configurations in cellular network in order to mitigate service disruptions during planned upgrades.

During eNodeB service disruption, some UEs (user equipment, such as a smartphone) experience degraded services. Neighboring eNodeBs can be re-configured to mitigate the degradation, for example, by changing *power attenuation* levels, which govern the transmit power of the radio. An eNodeB can increase the transmit power for higher SINR and thus provide better performance for its UEs. However, such changing needs to be done carefully because it introduces interference to UEs served by other eNodeBs [18, 31].

In a later section, we also discuss and evaluate another configuration parameter, *antenna tilt*. Antennas can be electronically tilted up or down to, respectively, increase or decrease the coverage area of the base station. The experimental hardware we use in this section does not support tilt, but operational cellular base stations do.

In this section, we experimentally explore the opportunity of minimizing the impact of such service disruptions by adaptively reconfiguring the cellular network parameters. For this, we use an LTE testbed, in which we consider various topologies. There are two advantages to experimenting with a real cellular deployment: (a) we can observe the practical impact of service disruption on UEs; and (b) we can practically evaluate the possibility of the network in continuing to offer high-quality service via adaptive reconfiguration.

Our measurements provide the following insights. First, whenever an eNodeB is taken offline, UEs can experience significant performance degradation, some may completely lose network connectivity, or may experience a throughput drop. Second, in many cases, tuning the transmission pa-

rameters of neighboring eNodeBs (such as their transmission power) can significantly mitigate the effects of service disruption. In what follows, we first discuss our experimental setup and then elaborate on our measurement-driven insights.

#### 3.1 LTE Testbed

Our testbed is a full-featured LTE Release-9 network that consists of 4 eNodeBs, 10 UEs and an Evolved Packet Core (EPC) deployment. The testbed is deployed indoors in the 4th floor of a corporate building.

**eNodeB:** Each eNodeB is a re-programmable Cavium LTE small cell [6] that carries an Octeon Fusion chip and runs Linux. We use an exclusive 10-MHz experimental license for transmission in band 7, where the downlink and uplink frequencies are centered at 2635 MHz and 2515 MHz, respectively. Each eNodeB carries a band-7 radio daughter-board with a transmission power that can reach up to 125 mWatts. Tuning of the transmission power takes place by tuning a software based attenuator; the attenuation (L) can take values starting from 30 (maximum attenuation - minimum power) down to 1, and can be tuned with a step as small as 1. All LTE transmissions are over the air using omni-directional antennae. We have verified that there is no external interference in our testbed.

**UEs:** The 4 eNodeBs serve 10 UEs deployed randomly in the same area. Each UE is hosted by a Core-I3 Intel NUC box with 4 GB memory that runs Ubuntu 14.04x64 Linux. The UEs are Sierra Wireless Aircard 330u USB dongles.

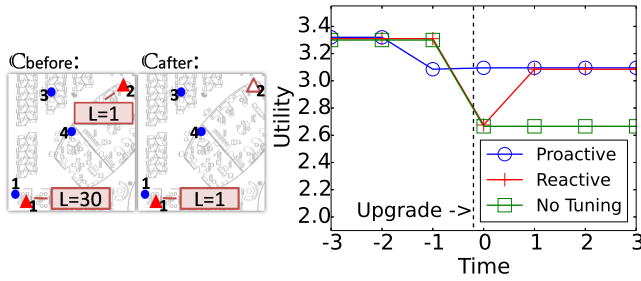
**EPC:** We use the Aricent EPC R2.1.0 software. Our EPC includes MME, SGW, PGW, HSS and PCRF elements [9]<sup>3</sup>. We have configured the access point name (APN) in the EPC to always set up bearers with QCI=9 for all UEs, which provides best effort service.

#### 3.2 Measurements and Observations

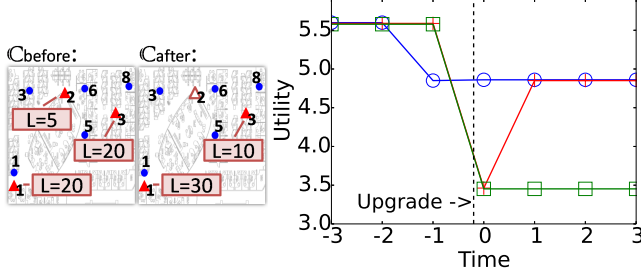
**Methodology.** We consider two different eNodeB service disruption scenarios. For each scenario, our goal is to empirically assess whether the network can be reconfigured such that users originally served by eNodeB(s) taken offline can be re-attached to one of the active eNodeBs. Thus, in each experiment, we first find the power configuration setting where the highest utility is achieved under normal conditions, i.e., in the absence of service disruption. Then, we take the eNodeB offline, and enumerate different power levels for the remaining active neighbor eNodeBs in order to maximally increase utility.

In these experiments, our measure of utility of a configuration is the sum of the logarithms of the UE downlink rates [22]:  $f(\mathbb{C}) = \sum_{x \in UEs} \log(r(x))$ , where  $\mathbb{C}$  is the set of power attenuation levels of all eNodeBs (i.e., the configuration of the eNodeBs) and  $r(x)$  indicates the downlink rate of UE  $x$ . This metric was chosen to indicate how well outage is mitigated. It balances the throughput performance while

<sup>3</sup>These acronyms refer to various services configured in the software. These services provide mobility management, gatewaying between the base station and cellular users and between the base station and the external IP network etc.



Scenario 1: The case for 2 eNodeBs, where eNodeB-2 is taken offline.



Scenario 2: The case for 3 eNodeBs, where eNodeB-2 is taken offline.

**Figure 2**—Demonstration of performance improvement using LTE Testbed. The left figure shows the configuration setting before and after the upgrade; the right figure shows the corresponding performance impact.

seeking fairness for users who are disadvantaged. Compared to a simple “sum of rates”, the log property provides a higher incentive to improve low rates of users experiencing poor radio conditions due to outage. This metric is associated with proportional-fair scheduling which is widely used in cellular systems. Our goal is to find the configuration with maximal utility.

During each experiment: (a) we first let the UEs attach to their preferred eNodeB, (b) then, we initiate simultaneous 30-sec downlink TCP traffic sessions from the application server towards each UE, (c) we measure the average downlink TCP throughput, and (d) we change the attenuations of eNodeB transmitters and repeat the above steps until we reach  $\max\{f(\mathcal{C})\}$ . We use *iperf* to measure the downlink throughput for TCP traffic flowing from an application server that is connected to the eNodeB to the UEs. During each experiment we capture  $\mathcal{C}_{before}$  and  $\mathcal{C}_{after}$ , and  $\mathcal{C}_{upgrade}$ .

**Scenario 1: 2 eNodeBs.** We first consider a simple scenario with 2 eNodeBs, where one of them needs to be taken offline, shown in Figure 2 Scenario 1 (left). Here, eNodeB-1 and eNodeB-2 serve UE-1, UE-3 and UE-4, and we need to take eNodeB-2 offline. Prior to service disruption, eNodeB-1 uses power attenuation  $L=30$  and eNodeB-2 uses  $L=1$ . With this,  $f(\mathcal{C}_{before}) = 3.31$ .

After we take eNodeB-2 offline, the best configuration setting  $\mathcal{C}_{after}$  is achieved by setting  $L=1$  at eNodeB-1, i.e., by maximizing its transmission power. This makes  $f(\mathcal{C}_{after})$

3.09. On the other hand, if there were no attenuation change at eNodeB-1 during service disruption, then the resulting  $f(\mathcal{C}_{upgrade})$  would be only 2.68 instead<sup>4</sup>. This is depicted in Figure 2 Scenario 1 (right). If we “proactively” tune the attenuation of eNodeB-1 to the optimal value by the time we take eNodeB-2 offline, the best achieved performance ( $f(\mathcal{C}_{after})$ ) is achieved faster than with a “reactive” strategy, where eNodeB-1 increases its power progressively after the service disruption.

In this scenario, the attenuation tuning decision for eNodeB-1 is straightforward: eNodeB-1 should use its highest power level since there is no interference from neighboring eNodeBs. Our next scenario considers a setting where interference plays a key role.

**Scenario 2: 3 eNodeBs.** As shown in Figure 2 Scenario 2 (left), eNodeB-1, eNodeB-2 and eNodeB-3 serve UE-1, UE-3, UE-5, UE-6 and UE-8. Assume that eNodeB-2 needs to be taken offline for maintenance. Under normal conditions when all 3 eNodeBs are online, the optimal power level configuration is achieved by tuning the individual attenuation levels as follows:  $L=20$  for eNodeB-1,  $L=20$  for eNodeB-3 and  $L=5$  for eNodeB-2. After eNodeB-2 is taken offline, we find that, in order to maximize our utility metric,  $\mathcal{C}_{after}$ ,  $L=30$  (the minimum transmission power) for eNodeB-1 and  $L=10$  for eNodeB-2. For this configuration, the resulting utility  $f(\mathcal{C}_{after}) = 4.85$ , and in the absence of tuning it would be  $f(\mathcal{C}_{upgrade}) = 3.46$ . This illustrates that, in the presence of interference, power attenuation levels must be carefully chosen in order to maximize utility (Figure 2 Scenario 2), and that the resulting utility is higher than without tuning.

These experiments demonstrate that tuning the transmission power levels of active eNodeBs when a neighboring eNodeB is taken offline can improve the network performance. Moreover, if one knew a priori the optimal values of the attenuation levels that need to be applied upon service disruption, then the proactive re-configuration of those values could alleviate the impact of the disruption to the user quality of experience. *How can we know these values in advance?* We address this question in the next section, where we propose a novel, accurate model-based approach for proactively deriving such values.

## 4. CELLULAR NETWORK MODEL

In this section, we describe the model Magus uses to analyze and estimate the throughput and coverage of a specific configuration of cellular network. Since we consider the impact of one or part of base station<sup>5</sup> being taken out of service, our model is designed to faithfully represent signal coverage and user throughput, while taking into account interference across sectors. In this paper, we focus on downlink rates, although our methodology can also be used for uplink performance.

<sup>4</sup>Small changes in the utility function are significant, since the function computes the sum of the *logarithm* of the rates.

<sup>5</sup>One base station usually contains multiple (typically 3) sectors, facing at different directions.

The unique aspect of Magus's model is that it is data-driven, and uses data that is available to a cellular network operator. The radio path loss is a critical characteristic, and a major contribution of our work is to use realistic operational data for transmit powers and radio path loss. While this operational data is used for planning purposes by many network operators, it is *not used for online re-configuration* in large carriers, to the best of our knowledge.

We first describe Magus's coverage and capacity model at a high level, followed by details of the operational path loss data we use to realize the analysis model, and a visualization of sector regions.

## 4.1 Cellular Coverage and Capacity Model

Cellular network coverage is often modeled and measured based on a geographical grid. We thus divide the area we want to analyze into grids, and assume users within the same grid perform equally.

The performance of a cellular network is determined by the rate enjoyed by each user. Magus models the user's rate based on two factors (a) radio link quality, and (b) sector load. The maximum rate that a user can sustain depends on the quality of the radio link and we model that as a direct function of the UE's SINR. This is also the user rate if the serving sector serves no other users. The actual rate observed by a UE in a loaded sector is lower than the maximum rate by a fraction that is directly related to capacity sharing. We provide details in the following subsections.

**Path Loss and SINR Calculation.** There could be more than one (typically 3) sectors at the same base station aimed in different directions covering adjacent sectors. The radio signal transmitted from a sector is attenuated due to the loss along the radio path to the user. In the model, the entire region is partitioned into rectangular grids, and the most important metric is the matrix of the *path loss* values (typically expressed in *dB*) from each sector to each geographical grid. If each sector  $b$  transmits with power  $P_b$  (*dBm*) and tilt  $T_b$ , the path loss to grid  $g$  is  $L_b(T_b, g)$  (*dB*). Magus computes the *Received Power* (RP) (*dBm*) at each grid  $RP_b(g)$  for the transmission from each sector  $b$ , as follows:

$$RP_b(g) = P_b + L_b(T_b, g) \quad (1)$$

To compute SINR for a given grid, we need the *RP* values from all the sectors. The sector that provides the best RP (denoted by  $RP_{best}$ ) becomes this grid's serving sector, and  $RP_{best}$  is thus the *signal*; the RPs from other sectors become *interference*. The SINR can then be calculated as follows:

$$\begin{aligned} SINR(g) &= \frac{RP_{best}(g)}{Noise + Interference} \\ &= \frac{RP_{best}(g)}{Noise + \sum_b RP_b(g) - RP_{best}(g)} \end{aligned} \quad (2)$$

**UE's Maximum Rate and Actual Rate.** From each grid's SINR, Magus can compute the maximum rate of a UE (denoted by  $r_{max}(g)$ ) in this grid, which is the user rate if there is no other user being served by that sector. We assume the cellular system is based on the 3GPP LTE standard. In our model, we look up the corresponding Modulation and Coding Scheme (MCS) index for a given SINR value ([5]), and

then look up the Transport Block Size (TBS) index ([2] Table 7.1.7.1-1) and finally the Transport Block Size ([2] Table 7.1.7.2.1-1) to map the SINR to the rate  $r_{max}(g)$ . There is a SINR threshold  $SINR_{min}$  to provide the minimum service, and if the SINR is less than  $SINR_{min}$ , we conclude that the grid is out of service with  $r_{max}(g) = 0$  for that condition.

The rate  $r_{max}(g)$  is achieved if there are no other users. If the sector serves multiple UEs, the capacity is shared by the users. For scheduling schemes such as round-robin, and proportional-fair (in the long term average), capacity is shared uniformly. The actual rate that one UE in this grid can achieve equals the maximum rate divided by the number of UEs the sector is currently serving. If we use  $N(g)$  to denote the number of UEs that  $g$ 's sector serves,  $\mathbb{G}$  to denote all the grids, and  $UE(x)$  to denote user numbers in grid  $x$ , then  $N(g)$  equals the sum of the number of UEs in all the grids that served by  $g$ 's sector:

$$N(g) = \sum_{x \in \mathbb{G}} (UE(x) \cdot \mathbf{1}_g(x)) \quad (3)$$

where indicator  $\mathbf{1}_g(x)$  indicates whether grid  $x$  and grid  $g$  are served by the same sector or not.

Then the actual rate for grid  $g$  is just<sup>6</sup>:

$$r(g) = \frac{r_{max}(g)}{N(g)} \quad (4)$$

We have described how Magus uses grid level information to model the rate for all the UEs. For a given scenario, Magus computes all grid level information: best sector, corresponding signal RP, the interference, SINR, and the number of UEs it contains; and sector level information: a list of serving grids, and the total number of served UEs (Figure 6).

The model above is deliberately simple, and it serves to validate our approach. More sophisticated models can be easily added if needed, and exploration of this is left to future work. The model's simplicity is dictated by the characteristics of the operational data used to drive the model. This is the most novel aspect of our work: while operational data has been used before for network planning, we believe it is not used for dynamic re-configuration in cellular networks.

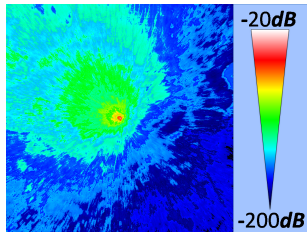
## 4.2 Operational Data Used in the Model

**Path Loss Data from Operational Networks.** In Formula 1, most analytical research assumes some classical model for path loss information  $L_b$ , e.g., attenuation as a function of link distance, frequency, antenna heights and empirical constants. However, state of the art path loss modeling in modern cellular networks includes details such as terrain, buildings, foliage, etc, and this detail is treated differently for each geographical grid region. The data we use comes from such a modeling tool called Atoll [7]. Path loss values are derived by using a Standard Propagation Model which is based on classical distance, frequency, antenna height models, which are then modified with empirical constants to capture terrain, foliage, and clutter effects for each grid.

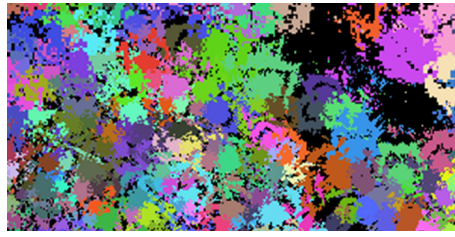
Instead of making simple assumptions for the attenuation, Magus uses *operational network path loss data*, which contains path loss information for a large US mobile carrier

<sup>6</sup>We assume there is no overheads involved in resource sharing.





**Figure 3**—Demonstration of operational network path loss data. Each pixel represents a grid. Brighter color indicates lower path loss and better receive power.



**Figure 4**—Demonstration of the service coverage map. Grids that are served by the same sector are painted in the same color. Black pixels indicates the grids that have receive power below a threshold.



**Figure 5**—Service coverage map (Figure 4) on top of the satellite map. The grids that have good receive power (higher than a threshold) are highlighted in red. The un-highlighted grids are sparsely inhabited areas.

network. In the model, each sector's path loss data covers a  $60\text{km} \times 60\text{km}$  square area, centered at the sector's location. This area contains  $600 \times 600$  grids, with a grid size  $100\text{m} \times 100\text{m}$ , and there is one path loss reading for each grid, resulting in one path-loss matrix (containing  $600 \times 600$  path loss values, in  $\text{dB}$ ) per antenna tilt configuration. This path loss data is refreshed periodically as needed and Magus always uses latest path loss data to build the model.

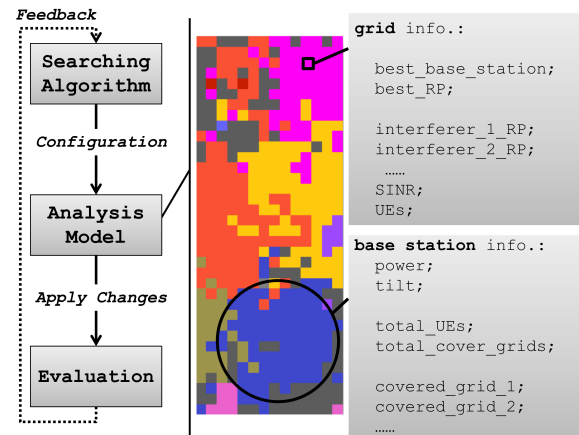
Figure 3 shows the path loss data of one sector in a metropolitan area. The path loss values range from  $-20\text{dB}$  for locations close to the sector to  $-200\text{dB}$  at the boundary of the area. As we can see clearly, this sector antenna is directional and pointing in the north-west direction. We can also see that the path loss data contours are irregular, and thus cannot be represented easily by simple equations.

**Base Station's Location, Transmission Power and Tilt.** Network operators choose base station locations, sector transmission powers and tilts carefully to provide better cellular service. In Magus, we use the actual locations, transmission powers and tilts of sector for Formula 1.

**UE Distribution.** Ideally Magus could use, as input, the number of UEs in each particular grid from operational data for Formula 3. We did not have fine-grained LTE UE distribution data available at the time we wrote the paper. As an alternative, we make a simple assumption: all grids served by a particular sector contain the same number of UEs (i.e., UE distribution follows a uniform distribution at the sector level). Thus, the number of UEs in each grid is obtained by dividing the total amount of UEs served by the sector by the number of grids that the sector serves. That said, if finer-grain information about UE distribution across grids were available, we could easily incorporate this into our model, and we have left this extension to future work.

### 4.3 Cellular Coverage Illustration

Figure 4 shows the predicted service map for a  $300\text{km} \times 150\text{km}$  area, derived from the Magus model. Each pixel represents a grid, and grids with the same color clustered together are served by the same sector. Black pixels represent the grids where SINR is lower than the  $\text{SINR}_{\min}$  threshold we choose, and we have intentionally chosen a high SINR threshold to show the clear difference between grids that receive good service and other grids. In Figure 5, we show an overlaid satellite map of the same area and highlight grids



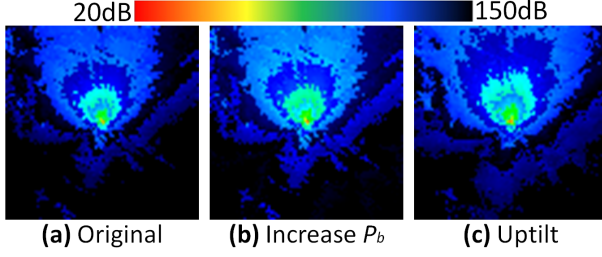
**Figure 6**—Magus's workflow. The search algorithm picks one potential configuration change; the analysis model applies the change by recomputing grid level and base station level information; the evaluation module then evaluates the performance and thus decides whether to accept this change or not.

having service in red. We see that our model matches the real map nicely, clearly bringing out coverage holes in sparsely inhabited areas (top-right corner of Figure 5). A more complete model validation is logistically difficult, since it would require extensive measurements from UEs in known locations. However, we are confident of the model accuracy since the data for the model comes from data used operationally for network planning, and the model itself relies on well-studied methods in cellular modeling.

## 5. SERVICE DISRUPTION MITIGATION

In this section, we discuss how Magus leverages the cellular network model to mitigate any service disruption due to sectors being taken down during network upgrade. It achieves this by finding the best power and tilt configuration setting  $\mathcal{C}_{\text{after}}$ . Note that, Magus's tuning approach is model-based and proactive, and thus different from dynamic power control optimization techniques like [14] that are reactive.

Figure 6 shows the components of Magus. The *Search Algorithm* searches for a good configuration, which is fed as an input to the *Analysis Model* (described in Section 4), which analyzes the rates achieved by users in the selected configuration. Finally, the *Evaluation* component determines the



**Figure 7**—Path loss of changing power and changing tilt, brighter color means lower path loss and hence good receive power. (a) path loss before change; (b) after increasing the transmission power; (c) after an antenna up-tilt.

goodness of the configuration. This component can also provide feedback to guide the selection of configurations iteratively until Magus converges to a satisfactory configuration.

**The Evaluation Component.** Magus’s optimization goal is to provide cellular coverage to all UEs while achieving the best *overall performance of all the UEs*. There is always a trade-off in cellular system between coverage, throughput, and fairness. We formulate the optimization goal in two steps: 1) we calculate a utility value for each UE based on the value of its actual downlink rate; and 2) we calculate the overall utility based on the utility values of all the UEs.

The utility function depends on the rate  $r$ . We use  $u(\cdot)$  to denote the utility function. Thus a UE with rate  $r_C$  for a particular configuration  $C$  has the utility given by  $u(r_C)$ <sup>7</sup>. We use  $\mathbb{U}(C)$  to denote the set of utility values of all the UEs for configuration setting  $C$ , then we have:

$$\mathbb{U}(C) = \{u(r_C(UE_1)), u(r_C(UE_2)), u(r_C(UE_3)), \dots\}$$

The optimization goal, then, is just to maximize the overall utility  $f(\cdot)$ , of  $\mathbb{U}(C)$ :

$$\max_C \left( f(\mathbb{U}(C)) \right)$$

We have not defined a UE’s utility function  $u(\cdot)$  and overall utility function  $f(\cdot)$  yet. It is desirable for  $f(\cdot)$  to be additive where the overall utility is a sum of the individual utility values for each user.

Magus can actually use different  $u(\cdot)$  and  $f(\cdot)$  for different mitigation purposes. For example, to maximize coverage, i.e., provide more UEs with qualified service, Magus can use a binary utility function  $u(\cdot)$  indicating whether the service is qualified or not:

$$f(\mathbb{U}) = \sum_{u \in \mathbb{U}} (u(r)), \quad u(r) = \begin{cases} 1, & r > 0 \\ 0, & r \leq 0 \end{cases} \quad (5)$$

If the goal is to maximize performance, we can use the metric described in Section 3, the “sum of the logarithm of the UE rate” [22]. Then we have:

$$f(\mathbb{U}) = \sum_{u \in \mathbb{U}} (u(r)), \quad u(r) = \begin{cases} \log(r), & r > 0 \\ 0, & r \leq 0 \end{cases} \quad (6)$$

**Base Station Configuration Tuning.** Restoring service for a sector suffering outage typically requires that there be adequate radio signal coverage in the affected grids. There are

<sup>7</sup>More precisely, rate information is at a grid level, so  $r(\cdot)$  should take the grid as input but not UE. To simplify notation, here we skip the step of getting the grid of the UE.

two sector parameters that can be tuned to increase signal coverage: (i) *Power*: the transmission power of the neighboring sector can be increased, and/or (ii) *Tilt*: the antenna of the neighboring sector can be tilted vertically upwards (uptilt) to shift the radio energy towards the target grids. Figures 7 (a), (b) and (c) illustrate the signal coverage of a sector before tuning, after a power increase, and after an uptilt, respectively. Below, we discuss algorithms for tuning power, tilt, and both power and tilt jointly.

**Search Algorithm Component.** To search for the best configuration, the simplest option is to use brute force, which tries all the configuration settings. However, this does not leverage useful information from the analysis model, and wastes time computing configurations which cannot mitigate induced performance impact, e.g., tuning a sector far away from the target sector or a sector facing in the opposite direction. To illustrate the huge search space, even if we only consider the nearby sectors, say, 10 sectors, and each sector can increase its transmission power by 5 units, we have to explore more than 9 million ( $5^{10}$ ) different configurations in this simple example.

In this paper, we propose a heuristic iterative search algorithm that leverages the unique nature of our problem and the observations of the radio network:

**i:** The initial setting  $C_{before}$  is a good place to start since it provides coverage to all the sectors around the target sector. Given how cellular networks are planned, users in the target sector are likely to get some level of coverage from the neighboring sectors.

**ii:** From this configuration, we use the analysis model to make stepwise changes to find a better configuration by making changes that can at least benefit some grids.

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#### Algorithm 1 : SEARCH ALGORITHM

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**INPUT:**

- i: involved sectors  $\mathbb{B}$ ;
  - ii: affected grids  $\mathbb{G}$ ;
  - 1:  $\beta = \emptyset, T = 1$
  - 2: **for all**  $g \in \mathbb{G}$  **do**
  - 3:   **for all**  $b \in \mathbb{B}$  **do**
  - 4:     **if**  $r_{C \oplus P(b,T)}(g) > r_C(g)$  **then**
  - 5:        $\beta = \beta \cup \{b\}$
  - 6:     **endif**
  - 7:   **endfor**
  - 8: **endfor**
  - 9:  $b_{best} = \arg \max_{b \in \beta} f(C \oplus P_b(T))$
  - 10:  $C = C \oplus P_{b_{best}}(T)$
  - 11: update  $\mathbb{G}$
  - 12: **goto 2:** (increment  $T$  if needed)
- 

**Transmission Power Tuning.** Specifically, our search algorithm starts from the  $C_{before}$  (i), and only tries configurations that can improve the SINR of at least one grid (ii). Algorithm 1 illustrates the important steps in Magus’s search component for tuning power.

Let mark  $\oplus$  denote a configuration change and  $C \oplus P_b(\Delta)$  denote a new configuration in which sector  $b$ ’s transmission power has been changed by  $\Delta$ . The algorithm takes as input the set of all the involved sectors  $\mathbb{B}$  in this scenario, which is chosen to be the set of neighbors of the sector(s) being



upgraded. Another input is the set of all the grids whose rate performance is degraded as a result of taking down one or more sectors,  $\mathbb{G}$ .

In each iteration, the algorithm calculates  $\beta$ , which is a set that contains sectors that can improve the SINR performance of some grid;  $\beta$  is empty initially. For any grid  $g \in \mathbb{G}$ , lines 4 and 5 identify all the sectors, that can improve  $g$ 's SINR with  $T$  units<sup>8</sup> of transmission power change with an initial condition of  $T = 1$ .

These promising configuration changes in  $\beta$  are “conditionally” good because, although they can improve some grids’ SINR, they can also decrease other grids’ performance, e.g., introducing more interference to some other grids that are not served by this sector. To see whether some of the potential changes in  $\beta$  are “globally” good, line 9 checks their overall utility by using the Evaluation component, and keeps track of the sector that provides best utility improvement,  $b_{best}$ . Then the algorithm applies the new configuration, updates the affected grid set  $\mathbb{G}$ , and moves on to the next iteration. If  $\beta$  is  $\emptyset$ , we increment the tuning unit  $T$ . This process terminates when we have re-covered all the grids that see degraded performance, or there is no sector can further improve the overall utility.

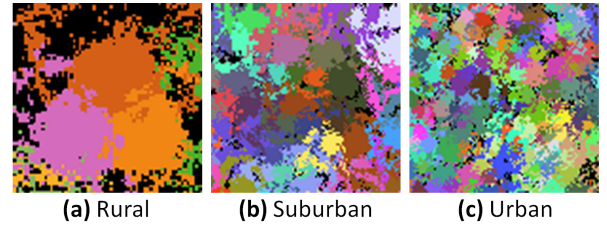
We have also left to future work an understanding of this algorithm’s stability properties as well as its relationship to an optimal strategy. Despite this, as we show later, Magus provides significant gains in coverage and performance relative to naive strategies.

**Antenna Tilt Tuning.** The basic methodology discussed above extends to exploring different tilt configurations. Conceptually, we can compute path loss models for each sector of each sector for all possible tilt settings (operational Atoll data [7] contains 16 different tilt settings besides the normal case). Once we have these, we can effectively replace the test in step 4 of Algorithm 1 to check whether tilting  $b$  by a specific tilt setting improves the rate.

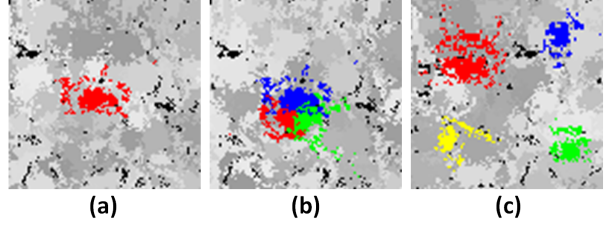
For logistical reasons, we chose a simpler approach that approximates the effect of tilting, but is more computationally efficient (and have left it to future work to explore a more faithful tilting model). First, our approach makes the simplifying assumption that the change to a path loss matrix caused by a specific uptilt or downtilt is the same across all sectors. This allows us to compute one change matrix for each uptilt or downtilt across all sectors (rather than computing a separate path loss matrix for each sector and tilt setting pair). Second, rather than search across all sectors in  $\mathbb{B}$  to find the optimal combination of tilt setting, we use a greedy algorithm: we incrementally uptilt the first neighboring sector until we reach a point where the utility becomes worse, then we uptilt the second sector, and so on.

**Joint Tuning.** Shown in Figures 7(b) and (c), tilt and power tuning produce different coverage results, so combining the two can potentially provide better results. In our evaluations, we explore the benefit of first employing tilt-tuning, followed by power-tuning. More elaborate joint optimizations are possible, and we have left an exploration of this to

<sup>8</sup>One unit is to increase the transmission power by 1dB.



**Figure 8**—Coverage map of three different types of areas. An urban area contains a lot more base stations than rural area.



**Figure 9**—Three different upgrade scenarios: (a) upgrading one sector at the center, (b) upgrading three sectors of one base station, and (c) upgrading four sectors at the four corners of the area.

future work.

## 6. EVALUATION

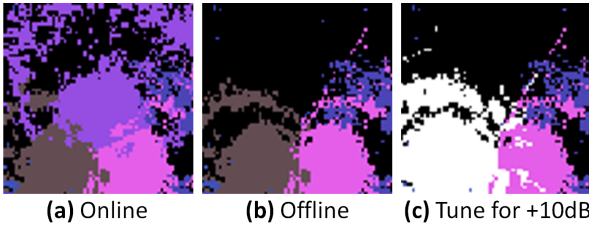
In this section, we first describe our evaluation methodology, then evaluate various properties of Magus.

**Evaluation Methodology.** Our evaluation uses operational cellular network data (base station locations, user density estimates and path loss information) for three different markets in the United States (a market roughly corresponds to the greater metropolitan area surrounding a major city). In each market, we evaluate Magus on a few  $10\text{km} \times 10\text{km}$  areas, exploring several planned upgrade scenarios in each region (described below). For each upgrade scenario, we tune sector configurations within the area, but we expand our analysis area to a larger  $30\text{km} \times 30\text{km}$  region to avoid boundary effects.

Since the trade-offs in radio network coverage can vary significantly with the radius of sectors, we select three different types of areas: *rural*, *suburban* and *urban* areas. Figure 8 shows a service map example for each of them. The density of sectors are quite different across the cases: in our experiments, we observe on average 26 sectors that interfere with the sectors in our rural area, 55 that interfere with the sectors in the suburban area and 178 that interfere with the sectors in the urban areas.

For each region, we attempt three different upgrade scenarios, shown in Figure 9: (a) upgrading a single sector at a centrally-located base station, (b) upgrading three sectors located at the same central base station, and (c) upgrade four sectors at the four corners of the region. The first scenario reflects a planned upgrade on a single sector at one base station, the second reflects upgrading the entire base station, and the third reflects a multi-sector concurrent upgrade.

We use a *recovery ratio* metric to evaluate the mitigation



**Figure 10**—Illustration of coverage of tuning neighboring sector in rural area: (a) before taking down the target sector; (b) after taking down the target sector; (c) after increasing one neighboring sector’s transmission power by 10dB.

performance achieved by tuning to the  $\mathbb{C}_{after}$  network configuration. This ratio is defined as:

$$\frac{f(\mathbb{C}_{after}) - f(\mathbb{C}_{upgrade})}{f(\mathbb{C}_{before}) - f(\mathbb{C}_{upgrade})} \quad (7)$$

The denominator is the degradation in the global utility due to a configuration change to  $\mathbb{C}_{upgrade}$ , while the numerator is the amount by which the global utility improves from the degraded value due to a configuration modification made by Magus. Thus, the recovery measures the fraction of the degraded utility from the planned upgrade recovered by tuning. A ratio of 1 indicates full recovery to  $f(\mathbb{C}_{before})$  and 0 indicates no improvement from mitigation.

**Mitigation of Service Disruption.** We studied 3 different rural areas, suburban areas and urban areas (total 9 different areas) across three markets. For each area we analyzed 3 different upgrade scenarios, for a total of 27 different scenarios. Our results are averaged and summarized in Table 1. The table shows recovery ratio results for power-tuning, tilt-tuning, and joint power-/tilt-tuning.

**Power-Tuning.** Table 1 shows that, across all areas in all three markets, Magus is able to recover at least 10% and up to 56% of performance by only tuning power. This is encouraging: from a cellular network provider perspective, any recovery is beneficial since it means smaller impact on customers.

It is interesting to note in Table 1 that the greatest gains are in suburban areas. This was, to us, an unexpected result. To a large degree, the efficacy of Magus is a function of the spare capacity available in neighboring sectors, and network capacity planners go to great lengths to place base stations to ensure adequate coverage. So, we expected that network planning would ensure uniform recovery regardless of the type of area. Yet, this result suggests that the resulting configurations are, in some areas, more effective at failure coverage than in other areas.

The reasons for the lower recovery in rural and urban areas are different. In rural case, the sector sizes tend to be large. The neighboring sectors are far away, and use up most of the available power to cover their sectors and are noise limited (the noise in Formula 2 becomes significant). In Figure 10, after the central sector is down, coverage cannot be recovered even if we increase the power of the closest neighboring sector (marked in white in (c)) by 10dB (10× power! and such increment probably already exceeds the maximum

transmission power of that sector). The maximum transmission power limit becomes a constraint. As a result, in rural cases, it is relatively harder for neighboring sectors to provide good service to grids served by the target sector.

The urban case is the opposite of rural case. There are several nearby neighboring sectors with enough power for their signals to reach the grids affected by the upgrade. However, urban radio networks are interference-limited, and severe interference to nearby grids limits the tuning potential. In addition, because sectors interact with many more neighbors, we may need to tune more sectors to get better results. For example, we may need to carefully tune neighbors of the sectors we are currently tuning. In these cases, our heuristic may get stuck at a local optima. We remind the reader that our first objective is to explore the viability of a model-based mitigation during a planned upgrade (to identify opportunities for improvement enabled by configuration tuning). A more sophisticated version of Magus (which we have left to future work) may do better.

In suburban areas, neighboring sectors can reach affected grids, and they are also relatively less interference-limited. So, there is room to tune neighboring sectors, and Magus indeed tunes more for suburban area cases.

In the three markets we study, nearly 49% of the areas are suburban, and only 6% are urban<sup>9</sup>. Thus, Magus, even in its present form, can be extremely effective in recovering performance loss due to a planned upgrade.

**Tilt-Tuning and Joint Tuning.** Table 1 shows that in general the recovery ratio of simply tuning tilt is not as good as of power-tuning. The reason is that tilt-tuning reshapes the angular distribution of radio energy without increasing total power; it reaches further at the cost of sacrificing nearby areas, and it does not increase radio signal in the side-lobe and back-lobe areas outside the primary zone of coverage. However, by combining the two, we see that the joint approach always performs better than power-tuning and tilt-tuning individually, improving performance by 2× over power-tuning. Our joint tuning algorithm is fairly simplistic, more sophisticated approaches might be able to improve recovery further.

From our current results, none of the upgrade scenarios offers consistently higher improvement than others across all areas. To understand whether one of these upgrade scenarios is statistically better than others would require evaluating a much larger number of areas, and we have left this to future work.

**Benefits of Gradual Tuning.** If we change the configuration from  $\mathbb{C}_{before}$  to  $\mathbb{C}_{after}$  in one step, many UEs need to handover to a different sector, and such handovers will happen simultaneously. This can introduce a significant signaling burden in the cellular network. Moreover, handovers are faster and incur less overhead when the source and destination sector are both online than when the source sector is taken offline. Based on these observations, we see value in tuning the configuration setting from  $\mathbb{C}_{before}$  to  $\mathbb{C}_{after}$  gradually, to avoid synchronized handover, and to provide as many

<sup>9</sup>We categorize areas by looking at the number of base stations this area contains.

Types of Tuning	Rural			Suburban			Urban		
	(a)	(b)	(c)	(a)	(b)	(c)	(a)	(b)	(c)
<b>Power-Tuning</b>	18.3%	17.5%	11.0%	56.5%	32.2%	24.5%	17.1%	22.7%	14.1%
<b>Tilt-Tuning</b>	8.4%	23.0%	9.3%	37.7%	27.9%	22.8%	8.8%	29.7%	3.8%
<b>Joint</b>	37.0%	28.9%	17.0%	76.4%	37.4%	38.8%	20.1%	32.0%	19.2%

**Table 1**—Experiment results for recovery ratio, calculated using Formula 7 and averaged for areas we studied. (a), (b) and (c) indicate different upgrade scenarios shown in Figure 9. For power-tuning, the greatest gains are in suburban area, gains for rural and urban areas are lower. In general, tilt-tuning cannot be as good as power-tuning, but the joint approach greatly improves the results of power-tuning.

UE as possible the opportunity of seamless handover before the sector upgrade.

A less-sophisticated approach can also reduce the power of the target sector gradually. But this does not guarantee the utility metric value, which could go through periods where the metric is even lower than the final  $f(\mathcal{C}_{after})$  scenario. Magus has an estimate of  $f(\mathcal{C}_{after})$ , so it can ensure that, throughout the gradual tuning process, the *overall utility is never less than*  $f(\mathcal{C}_{after})$ . Magus uses a greedy strategy in which it decreases the transmission power of the target sector (the one for which an upgrade is planned) in small steps well before the planned upgrade time. This will force a small number of UEs to migrate to neighboring stations. However, we make sure that the utility never goes below  $f(\mathcal{C}_{after})$ : if Magus predicts that it will, it tunes toward  $\mathcal{C}_{after}$  a bit to compensate, by either uptilt or increases the power of the neighboring sectors. The process terminates either when Magus cannot compensate (in which case it jumps directly to  $\mathcal{C}_{after}$ ), or when no UEs are left attached to the target sector.

Figure 11 demonstrates one example of gradual tuning. At each step, UEs re-attach to nearby sectors (handover) gradually, as opposed to the direct tuning case (Proactive) where all the UEs that need to handover do it simultaneously at the time of upgrade. Moreover, the utility never goes below  $f(\mathcal{C}_{after})$  (“^” marks the tuning steps we tune nearby sectors in Figure 11). With our approach, at any step, the largest number of simultaneous handovers we see is 2457; without, it is 9827. So, Magus can reduce simultaneous handovers by 3 $\times$ , and 99.7% of UEs can do a seamless handover (when the source sector is still on-line) instead of hard handover (when it is offline). Across all our scenarios, Magus reduces simultaneous handovers by a factor of 8, and enables 96.1% of UEs to achieve seamless handover.

**Speed of Convergence.** We compare our proactive model-based approach to a reactive feedback approach (Figure 12). We estimate the number of steps the reactive feedback approach needs to converge to the best configuration setting.

We assume a simple tuning strategy for the reactive feedback approach: it can only tune 1 power-tuning or tilt-tuning unit of one single neighboring sector in each step. To give benefit to this strategy, we set it up so that at each step it picks the best configuration (we use our model to determine this). Even under this idealized scenario, the reactive feedback approach still needs 27 steps to get the best configuration setting, in one of our upgrade scenarios. In practice, it could be a lot longer. We have estimated that a more realistic estimate for the same scenario is 310 steps. Taking into

account the time to obtain the feedback (extract performance measures from the sector) which can be on the order of several minutes, even the idealized reactive feedback based approach could recover performance only after two hours after the start of the planned upgrade.

**Flexibility of Using Different Utility Functions.** As discussed in Section 5, Magus can use different utility functions that specify different objectives. We illustrate this for a suburban area with upgrade scenario (a), use both the log-sum rate performance utility (Formula 5) and the coverage utility (Formula 6). Table 2 shows the recovery ratio for both met-

Optimization Utility Function	Recovery Ratio	
	$u_{performance}$	$u_{coverage}$
$u_{performance}$	66.3%	2.6%
$u_{coverage}$	-29.3%	14.4%

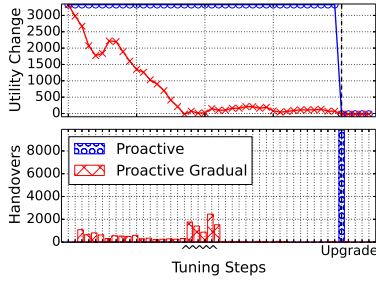
**Table 2**—Recovery ratio of one scenario, using different utility functions. Recovery ratio is calculated using Formula 7,  $u_{performance}$  and  $u_{coverage}$  are referring to utility functions of Formula 5 and 6 respectively. Different utility functions converge to different tuning changes, and Magus can choose different utility function based on requirement.

rics, and the achieved utilities. When the performance utility is used, 63.3% performance is recovered but only 2.6% coverage is recovered. Conversely, when the coverage utility is used, 14.4% coverage is recovered, but at the cost of performance. This illustration indicates that Magus can be used with different utility functions in different areas. In a rural area, providing coverage might be a priority, but in an urban area, performance might.

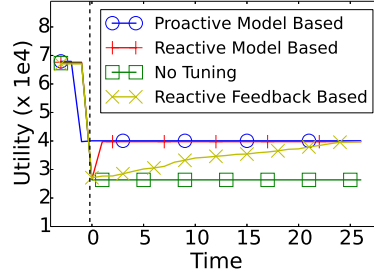
**Benefit of Search Heuristic.** To compare the quality of Magus’s ability to detect the best tuning configuration given a current configuration, we could have used brute force, but the search space is too large: even without tilt changes, if we tune only 10 sectors, and for each of them try 10 units of power change, our search space is 10 billion. For this reason, Magus contains a heuristic search strategy (Algorithm 1, which is for power-tuning only) that prunes the search space taking the problem structure into account. To demonstrate that this heuristic is better than simpler approaches, we compare it to a naive approach similar to the one we use for tilt-tuning: it increases transmission power by 1dB for the first neighbor at each step until utility worsens, then does the same for the second neighbor and so on.

For the 27 different scenarios we studied, we compare our solution to the naive approach’s solution, and calculate the improvement ratio, which is just  $\frac{\text{Magus recovery ratio}}{\text{naive recovery ratio}}$ . We plot

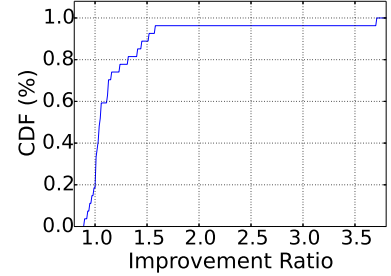




**Figure 11**—Benefits of gradual tuning (Proactive Gradual). Gradual tuning reduce simultaneous handovers by 3× and offer 99.7% of UEs a seamless handover.



**Figure 12**—Comparing speed of convergence across tuning approaches. Reactive Feedback Based approach takes much longer than other approaches.



**Figure 13**—Improvement ratio of Magus (Algorithm 1) on naive approach. Magus is better for 81% of scenarios, with maximum improvement ratio 3.87 and average improvement ratio 1.21.

the CDF in Figure 13. Among these 27 scenarios, our algorithm is no worse than the naive approach for 22 of scenarios, takes 81% of the scenarios we study. For those 5 scenarios that our algorithm performs worse, we still generate solution with similar recovery ratio (the improvement ratio is never below 0.9). For more than 22% of the scenarios, our solutions are 30% better than naive approach (improvement ratio greater than 1.3). For the best case, the improvement ratio is 3.87. Overall, our algorithm is 21% better than the naive approach.

## 7. RELATED WORK

To our knowledge, no prior work has examined network reconfiguration for planned upgrades. We have been inspired by prior work in three areas: upgrade management, modeling cellular networks and Self-Organizing Networks (SON).

**Upgrade Management.** There are several proposals and industry solutions for minimizing disruptions during planned upgrades in IP networks [15, 16, 34], data center networks [21, 25, 17] and Software Defined Networks [30, 21]. In cellular networks, Litmus [27] and PRISM [26] focuses on impact assessment of planned network changes. Our problem scope is different from the state-of-art solutions and managing upgrades for cellular networks brings in new sets of technical challenges such as its dependence on external environments, radio network configurations, and end-user workload and mobility patterns.

**Modeling Cellular Networks.** Researchers have made great efforts to understand the performance of cellular networks [19, 32, 12]. Because it is extremely hard to estimate end-user’s performance, people usually make some assumptions in their model. [23, 35, 24] model base station’s coverage range, treat locations within the coverage range equally, and use overlapping coverage areas to approximate interference and un-covered areas to approximate coverage holes. [20] assumes omni-directional base stations. [36, 14] make assumptions about the signal propagation model. On the other hand, Magus divides the coverage area into  $100m \times 100m$  grid and calculates each grid’s SINR and throughput rate independently. We also leverage operational network data and ATOLL-based coverage models to make Magus’s predictive model more realistic.

**Self-Organizing Networks (SON).** The idea of self orga-

nizing and optimization [14, 33, 29] envisions SON [1], which is designed to automate network configuration and optimization processes. It self-heals from network outages as discussed in 3GPP Release 10 [3] and prior work has explored Cell Outage Detection (COD), Cell Outage Recovery (COR) and Cell Outage Compensation (COC) [23, 35, 24, 3, 11, 4, 13, 28, 10]. Cell outage compensation algorithms tune the transmission power, antenna tilt and antenna azimuth angle for improving service performance during network outages. They are reactive and begin their tuning process after the occurrence of an outage. They completely rely on performance and configuration feedback from the field to make their tuning decisions. Magus on the other hand, does not rely only on feedback and uses predictive model-based approaches in a proactive manner to better manage service performance during planned upgrades. Magus also converges much faster than feedback-based approaches.

## 8. CONCLUSION AND FUTURE WORK

In this paper, we describe the design and evaluation of Magus that mitigates service disruption during planned upgrades. These occur frequently and can have a significant impact in modern cellular networks. To our knowledge, no prior work has explored this problem. During such upgrades, when a base station is taken off-air, users can re-attach to neighboring base stations, as our experiments on an LTE testbed demonstrate. Magus is a proactive model-based approach that predicts the near-optimal power and tilt configuration for neighboring base stations and then tunes these stations before the planned outage. Magus uses real operational network data such as base station location, configuration, and path loss information to achieve accuracy, and a heuristic search algorithm to converge to a near-optimal configuration for a given upgrade. Our experiments show that Magus can recover a significant fraction of lost capacity while also greatly reducing the number of synchronized handovers caused by the upgrade.

Several directions of future work exist: a field deployment, improved joint tuning techniques of power and tilt, using Magus’s predictive model for unplanned outages (using Magus’s computed configuration as a starting point for feedback control, and pre-computing configurations for different outages), or for load-balancing and reducing congestion.

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