Predicting the Performance of Cellular Networks: A Latent-resilient Approach

Kartik Patel[†], Changhan Ge[†], Ajay Mahimkar[§], Sanjay Shakkottai[†], Yusef Shaqalle[§]

[†] The University of Texas at Austin, Austin, TX, USA
{kartikpatel, chge, sanjay.shakkottai}@utexas.edu

[§]AT&T Labs, Bedminster, NJ, USA
{mahimkar, yusef.shaqalle}@att.com

Abstract

Cellular service providers (CSPs) require predicting the network performance for various reasons such as analyzing the impact of planned configuration changes and large-scale events on the network. Although network configurations are widely considered as key predictors of performance, we claim that they are insufficient for accurately predicting cellular network performance. The cellular networks are impacted by unmeasured external factors (*e.g.*, weather, called *latents*), therefore, the performance prediction based solely on configurations may result in confounding effects. We show that the *Mobility, Access, and Traffic (MAT) metrics* should be considered in addition as network performance predictors. Using a large dataset collected from a live cellular network, we validate the claim and show the benefit of using MAT metrics for accurate performance prediction.

CCS Concepts

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

Keywords

Network performance modeling, Network management

ACM Reference Format:
Kartik Patel[†], Changhan Ge[†], Ajay Mahimkar[§], Sanjay Shakkottai[†], Yusef Shaqalle[§]. 2024. Predicting the Performance of Cellular Networks: A Latent-resilient Approach. In *The 30th Annual International Conference On Mobile Computing And Networking (ACM MobiCom '24), November 18–22, 2024, Washington D.C., DC, USA.* ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/3636534.3697425

ACM MobiCom '24, November 18–22, 2024, Washington D.C., DC, USA

ACM ISBN 979-8-4007-0489-5/24/11...$15.00
https://doi.org/10.1145/3636534.3697425

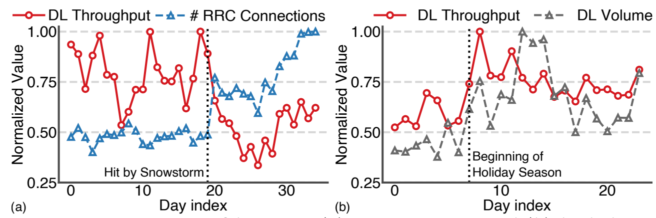

Figure 1: Impact of latents. (a) snowstorm and (b) holiday

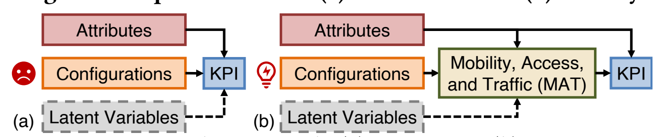

Figure 2: Dependency graph. (a) One-stage. (b) Two-stage.

1 Introduction

Accurate prediction of cellular network performance, measured by Key Performance Indicators (KPIs) like throughput, is crucial for efficient network management. Cellular service providers (CSPs) use these predictions to assess the impact of planned configuration changes and prepare for large-scale events such as concerts and sports events.

Traditional network performance prediction approaches consider the network configurations as primary predictors [3]. However, we argue that the configurations are insufficient predictors of KPIs due to the significant influence of external factors, called *latent variables*. These include weather conditions, environmental factors, and other unobserved influences that can significantly affect KPIs. As shown in Fig. 1, a snowstorm or a holiday break can significantly impact LTE cell throughput, even without changes to network configuration. Thus, latents present the challenge in accurately capturing the relationship between configurations and KPIs.

In theory, KPIs can be predicted using the values of configuration parameters and latent variables (see Fig. 2(a)). Unfortunately, exhaustively identifying and quantifying latent variables and their impact on KPIs is impractical.

To address this, we propose a latent-resilient approach that leverages the *observable* metrics, called *Mobility, Access, and Traffic (MAT) metrics*, to predict KPIs. MAT metrics are impacted by both configurations and latent variables, thus, can capture the variations associated with them (see Fig. 2(b)). Furthermore, MAT metrics are observable network metrics collected by CSPs, making them suitable for predictions.

Previous works [2, 4] correlate "LMRD parameters" (a subset of a combination of MAT metrics and attributes) with

LTE KPI x	Configuration $P = C$	MAT $P = \mathcal{M}$	NR KPI x	Configuration $P = C$	MAT $P = \mathcal{M}$
DL Throughput	0.2323	**0.6176**	DL Throughput	0.0959	**0.6641**
Retainability	0.2999	**0.4093**	Retainability	0.0512	**0.4613**

Table 1: CODEC score $\tilde{T}(x, P|\mathcal{A})$.

KPIs to recommend network configurations. However, they do not focus on predicting KPIs. We aim to show the utility of MAT metrics for predicting KPIs.

Contributions: *(i)* Through real-world LTE and 5G data, we prove that MAT metrics are better predictors of KPIs compared to configuration parameters. *(ii)* We develop a Deep Neural Network (DNN) model to accurately predict DL throughput using MAT metrics. *(iii)* As an example, we also describe the use of MAT metrics for the task of predicting the change in KPI due to configuration changes.

2 Dataset

A national cellular network is partitioned into multiple markets, each containing multiple base stations (BSs). Each BS contains multiple cells, the basic functional unit of a cellular network. We obtained daily cell-wise snapshots of network data from a top CSP in the US for four markets over a 20-month period. The dataset encompasses five data categories:

(1) *Cell attributes*, such as BS type, hardware, frequency, bandwidth and morphology, are relatively static parameters which define the operating characteristics of a cell. We denote the set of attributes by $\mathcal{A}$.

(2) *Cell configurations*, such as transmitted power, antenna tilt angle and handover thresholds, are used to tune the network depending on the deployment scenarios and requirements. We denote the set of 318 configurations by C.

(3) *MAT metrics* measure (i) User Equipments (UE) Mobility-related metrics such as UE distance and speed distributions, attempted and successful handovers; (ii) Cell Access-related metrics such as average signal strength; and (iii) Traffic metrics such as data volume and cell utilization. We consider 56 MAT metrics, denoted by $\mathcal{M}$.

(4) *Key Performance Indicators (KPI)* such as average per-user throughput, call retainability and call accessibility measure the quality of service experienced by the users.

(5) *Derived variables*, like the day of the week, represent periodic factors that can account for a part of the external influences on the network. They are not in the dataset but are calculated from dates and attributes.

Notably, the dataset does not contain latent variables, such as weather history and large-scale events (*e.g.*, sports) which can significantly affect KPI. Exhaustively logging all latents and quantifying their effects is a nearly impossible task.

3 Predicting KPI: Configurations or MAT?

3.1 Statistical validation

We use Conditional Dependence Coefficient (CODEC) [1] to statistically measure the conditional dependency between features (configurations or MAT metrics) and KPIs.

3.1.1 *CODEC score:*

Let the target variable be denoted by x and two disjoint sets of features be denoted by P and Q. Then, the metric $T(x, P|Q)$, that quantifies the dependency between x and P conditioned Q, is defined as follows [1]:

$$T(x, P|Q) = \frac{\int \mathbb{E}(\mathrm{Var}(\mathbb{P}(x \geq t|P, Q)|Q))d\mu(t)}{\int \mathbb{E}(\mathrm{Var}(\mathbf{1}\{x \geq t\}|Q))d\mu(t)}. \quad (1)$$

T can be viewed as the fraction of variance in x that is explained by (P, Q) but cannot be explained by Q alone [1].

From a statistical perspective, $T(x, P|Q)$ represents a theoretical limit on the predictive accuracy of a regression model that aim to predict x based on P, for a given Q. If $T(x, P|Q)$ is sufficiently large, then a good function approximator (such as a neural network) can find a mapping from P to x (for each value of Q) with a minimal error. Conversely, a low value of $T(x, P|Q)$ indicates that the variability in x cannot be adequately represented by a function of P alone (regardless of Q), rendering neural network training ineffective.

3.1.2 *Evaluation:*

Using CODEC score, we show that MAT metrics are better predictors of KPI compared to configurations. Specifically, we consider each KPI as a target variable x, and measure the degree of dependence (conditioned on attributes) between KPI and *(a)* configurations, i.e., $P = C$ and $Q = \mathcal{A}$. *(b)* MAT metrics, i.e., $P = \mathcal{M}$ and $Q = \mathcal{A}$.

As shown in Table 1, we observe that when the set P includes MAT metrics, the CODEC values are higher compared to when set P includes configurations. This means that MAT metrics encode more information about KPI which configuration parameters can not (see Fig. 2). Hence, we conclude that MAT metrics are better predictors KPIs than configurations.

3.2 DNN-based validation

3.2.1 *The structure of DNN:*

The architecture of our DNN is based on the observation that the relationship between KPI and MAT metrics can vary across different attributes in the cellular network. To accommodate this variability, we use a shared representation within our DNN model but with tunable heads for different attribute values. Our model takes both MAT metrics $\mathcal{M}$ and attributes $\mathcal{A}$ as inputs. It first categorizes attributes into (1) Mask attributes, and (2) Feature attributes. The mask attributes significantly influence the relationship between MAT metric and KPI, thus, requiring their own tunable heads. The feature attributes have lesser impact on the characterization and can act as a feature to the DNN model. We empirically determine the categorization between mask and feature-attributes. The main branch of the model takes MAT metrics and one-hot encoded feature attributes as inputs. It contains 7 fully connected hidden layers with leaky ReLU activation which forms a shared representation. Then the main branch is split into sub-channels for each value of mask attributes. Each sub-channel consists

Model	Mask/Feature Attributes (M/F)					MSE	wrt Variance = 0.015	
	DL MIMO Mode	Freq-uency	eNodeB Type	Hard-ware	Soft-ware		Residual Error	Improv-ement
One-stage	M	F	F	F	F	0.00638	42.54%	N/A
Two-stage (DNN)	F	F	F	F	F	0.00185	**12.34%**	**+30.20%**
	M	F	F	F	F	0.00197	13.10%	+29.44%
	M	M	F	F	F	0.00218	14.53%	+28.01%
	M	M	M	F	F	0.00204	13.62%	+28.92%
	M	M	M	M	M	0.00197	13.16%	+29.38%
Common Mask Attributes			Market, Morphology, Tower Height					
Common Feature Attributes			Weekday, Bandwidth					

Table 2: Achieved MSE. Models are jointly trained across 4 markets of LTE network with varied mask attributes.

of 2 fully connected hidden layers and one output layer. Finally, the mask selector chooses the final outputs from the channels depending on the value of the mask attribute.

3.2.2 ***Training methodology:*** We use a linear combination of MSE and Wasserstein distance as the loss function, which is given by $\mathcal{L}(\mathbf{y}, \hat{\mathbf{y}}) = \text{MSE}(\mathbf{y}, \hat{\mathbf{y}}) + 0.5\mathcal{W}_1(\mathbf{y}, \hat{\mathbf{y}})$. We choose 0.0005 as the initial learning rate and decrease the learning rate by a factor of 0.9 if the validation loss remains unchanged for 5 epochs. We use the batch size of 256 samples.

3.2.3 ***Evaluation:*** To achieve optimal performance of DNN, we explore various selections of the mask attributes. Mask attributes offer a mechanism for fine-tuning the model, enabling model optimization tailored to specific attributes. To this end, we experiment with the combinations of mask and feature attributes and summarize the MSE errors in Table 2.

While increasing the number of mask attributes theoretically enhances model accuracy, our results show a more nuanced relationship. We observe a consistent rise in MSE as the number of mask attributes increases, due to reduced training data for individual head layers, which decreases accuracy. This highlights the need for careful selection of mask attributes, prioritizing those with the strongest impact on the KPI-MAT relationship to optimize performance.

3.2.4 ***Comparison with one-stage model:*** Here, we use only configuration parameters and attributes to predict Downlink (DL) throughput for all date and cell combinations. We employ a DNN similar to the one described in Sec. 3.2.1, but with 152 neurons per layer to accommodate increased number of inputs. The market, morphology and tower height are designated as *mask attributes*, while hardware, software, enodeB type, frequency, MIMO mode and weekdays are considered as *feature attributes.* Following the training procedure described in Sec. 3.2.2, we find that the MSE of **One-stage** model and **Two-stage** model is 0.00638 and 0.00197, which corroborates with the fact that using MAT metrics with attributes are better predictors of KPI.

4 Assisting Configuration Tuning

CSPs frequently tune the configurations to optimize the network performance. To assist with the configuration changes, we design a MAT metrics-based toolkit, called Configuration Impact Prediction Analysis Toolkit (CIPAT), that can predict the performance impact of the configuration changes before implementing them on a live network. CSPs can use CIPAT to filter-out the configurations that may degrade the network performance and avoid testing them on the network.

Specifically, CIPAT takes two inputs: (i) the proposed configuration change, and (ii) the attributes of the cell where the change is being considered. The first stage of CIPAT predicts the direction of changes in MAT metrics resulting from the proposed configuration change and, subsequently, the range of potential values of MAT metrics. The second stage of CIPAT uses a DNN model to predict the change in KPI for all potential values of the MAT metrics. Finally, CIPAT compares the likelihoods of KPI improvement and degradation, and then recommends or warns CSPs about the potential impact of the configuration change. Therefore, CIPAT can answer one of the most important questions in cellular network management: *Should an operator go ahead with a configuration change on a live network?*

Our post-facto analysis using the real-world dataset show that CIPAT can successfully filter up to 86% of the configurations that degrade cell throughput. More importantly, CIPAT can filter up to 95% of the unobserved configuration changes (not observed in the training of CIPAT) that degrade the cell throughput. Thus, CIPAT can help reduce the number of live network tests with detrimental configurations [5].

5 Conclusion

This study demonstrates that configuration parameters are insufficient for predicting cellular network performance, and MAT metrics should be used instead. This observation holds tremendous value for CSPs in assessing performance impacts from factors such as configuration changes or large-scale events. To apply this insight, we propose a two-stage approach: CSPs should first evaluate how these events influence MAT metrics and then use a regression model, such as a DNN, to predict performance based on the MAT metrics.

Acknowledgements

This work is supported by NSF grants CNS-2107037 and CNS-2112471. Changhan Ge thanks Prof. Lili Qiu at UT Austin.

References

[1] Mona Azadkia and Sourav Chatterjee. 2021. A simple measure of conditional dependence. *The Annals of Statistics* 49 (2021), 3070 – 3102.

[2] Changhan Ge, Zihui Ge, Xuan Liu, and et al. 2023. Chroma: Learning and using network contexts to reinforce performance improving configurations. In *ACM MobiCom '23*. New York, NY, USA, 628–643.

[3] Herodotos Herodotou, Yuxing Chen, and Jiaheng Lu. 2020. A Survey on Automatic Parameter Tuning for Big Data Processing Systems. *ACM Comput. Surv.* 53, 2, Article 43 (Apr 2020), 37 pages.

[4] Ajay Mahimkar, Zihui Ge, Xuan Liu, and et al. 2022. Aurora: conformity-based configuration recommendation to improve LTE/5G service. In *ACM IMC '22*. New York, NY, USA, 83–97.

[5] Kartik Patel, Changhan Ge, Ajay Mahimkar, and et al. 2024. CIPAT: Latent-resilient toolkit for performance impact prediction due to configuration tuning. In *1st ACM Workshop on Machine Learning for NextG Networks* (Washington, DC, USA). ACM, New York, NY, USA, 6 pages.