Automating Diagnosis of Cellular Radio Access Network Problems

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ABSTRACT

In an increasingly mobile connected world, our user experience of mobile applications more and more depends on the performance of cellular radio access networks (RAN). To achieve high quality of experience for the user, it is imperative that operators identify and diagnose performance problems quickly. In this paper, we describe our experience in understanding the challenges in automating the diagnosis of RAN performance problems. Working with a major cellular network operator on a part of their RAN that services more than 2 million users, we demonstrate that fine-grained modeling and analysis could be the key towards this goal. We describe our methodology in analyzing RAN problems, and highlight a few of our findings, some previously unknown. We also discuss lessons from our attempt at building automated diagnosis solutions.

1 INTRODUCTION

Cellular Radio Access Networks (RAN) form the backbone of connectivity on the move for billions of Internet users everyday. Being such a crucial component in their network infrastructure, cellular network operators are constantly striving to operate RANs optimally so as to provide high quality of user experience (QoE) to their subscribers. To achieve high performance in RANs, it is imperative that operators understand the impacting factors and can diagnose performance problems quickly.

RAN performance diagnosis is hard. Factors impacting RAN performance include user mobility, traffic pattern, interference, coverage, unoptimized configuration parameters, inefficient algorithms, equipment failures, software bugs and protocol errors [9, 23, 24]. It is very challenging to diagnose these problems due to the fact that the performance of multiple base stations are coupled by the shared radio access media and user mobility. Existing systems [4, 11] for troubleshooting perform their function by monitoring key performance indicators (KPIs), i.e., aggregate counters such as connection drop rate and throughput per cell, over a several-minute time window. Persistent poor KPIs of base stations or base station clusters trigger mostly manual root cause analysis. This process is slow and ineffective. Often times there are disagreements on who should handle the trouble ticket, such as the RF team, the call processing team or the modem team. In addition, many of these tickets conclude that the problem occurred due to reasons already discovered by earlier analyses[1] *after* extensive troubleshooting. Even worse, a large number of these problems reoccur after fixing several times.

Can cellular network operators automate the detection and diagnosis of RAN performance problems? In this paper, we attempt to answer this question by reporting our experience working with a major cellular network operator. We have studied a portion of this operator's RAN that servers over 2 million subscribers for a period of over a year. During this tenure, we have seen the network experience thousands of problems, and the effort spent by the operator in solving them. Based on this experience, we propose a new methodology to diagnose RAN problems in a better fashion. Our approach is also amenable to automation.

A key problem of current systems stems from relying on aggregate KPIs, making it hard to isolate the many root causes contributing to the observed poor KPI. The natural solution to this problem is to use fine-grained information to do such diagnosis. However, it is infeasible to continuously log metadata for every transmission in the physical layer (e.g., SINR) or for every frame in the MAC layer (e.g., block error rate), or for every packet in the IP layer (e.g., headers). Instead, in this work, we propose using connection (bearer) level traces which can be feasibly collected in current operational networks. A bearer is a connection between a UE and the cellular network. Bearer level traces contain per-procedure (e.g., initial attach) information and aggregate data per bearer (e.g., total physical resources allocated, average uplink SINR).

Our methodology first segregates RAN performance problems based on the broad underlying root causes, and then builds detailed performance models at the bearer level. Assigning the problems to broad buckets allows us to generalize the approach to diagnose them. We distinguish two types of performance metrics. For *event-based* performance metrics such as connection failures and drops, we use classification techniques in machine learning, such as decision trees, to build models that explain the problem. For *volume-based* performance metrics such as radio link layer throughput, we build detailed information theoretic regression models based on physical and MAC layer information. Building these models are non-trivial due to the availability of only aggregate information at the bearer level and because the model needs to consider protocols in several layers. We further derive cell-level KPI models from bearer-level models. This enables us to attribute the root causes affecting bearer-level to their impact on KPIs at the cell-level (§3).

To validate our proposal, we have applied our methodology to the data collected at the operator's RAN, where it revealed several

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[1] e.g., we found multiple tickets that concluded that a particular device model caused load-balancing issues

MobiCom '17, October 16–20, 2017, Snowbird, UT, USA

ACM ISBN 978-1-4503-4916-1/17/10…$15.00
https://doi.org/10.1145/3117811.3117813

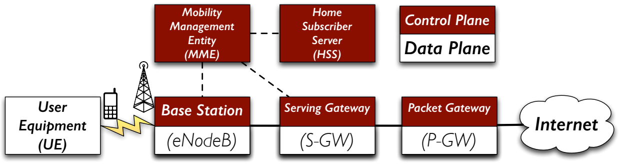

Figure 1: LTE network architecture

interesting insights (§4). First, we found that the detection of periodic channel quality indicator (P-CQI) feedbacks in the physical layer is unreliable. When the feedbacks are transmitted through uplink control channel, they are not protected by CRC. Since the base station only performs threshold-based detection, it could decode arbitrary values once the signal passes the threshold. Without the CRC, there is no way of knowing whether the decoded P-CQI is spurious or not. Coding redundancy can be applied to avoid most of these problems. However, we observed that these spurious P-CQIs are not negligible and causes many ongoing connections to drop. Second, the link adaptation algorithm in the physical layer is not efficient and results in poor throughput. Third, many connection failure alarms can be explained by known root causes. Some of these insights were not previously known.

Finally, while developing the diagnosis methodology and applying it on an operational network, we learned that while fine-grained analysis is tremendously useful, a fully automated diagnosis solution suitable for the next generation cellular networks requires solving several research and engineering challenges (§5).

2 BACKGROUND

In this section, we briefly review the LTE network architecture and its data collection mechanism to familiarize the reader with the basic entities in the network and the characteristics of the data available for RAN diagnosis. We also discuss how existing state-of-the-art RAN diagnosis systems function.

2.1 LTE Network Architecture & Protocols

LTE networks enable User Equipments (UEs) such as smartphones to access the Internet. The LTE network architecture is shown in fig. 1, which consists of several network entities. When a UE is in idle mode, it does not have an active connection to the network. To communicate with the Internet, a UE requests the network to establish a communication channel between itself and the Packet Data Network Gateway (P-GW). This involves message exchanges between the UE and the Mobility Management Entity (MME). The MME may contact the Home Subscriber Server (HSS) to obtain UE capability and credentials. To enable the communication between the UE and MME, a radio connection called radio bearer between the UE and the base station is established. GPRS Tunneling Protocol (GTP) tunnels are established between the base station and the Serving Gateway (S-GW), and between the S-GW and the P-GW through message exchanges involving these entities and the MME. The radio bearer and the two GTP tunnels make up the the communication channel between the UE and the P-GW called Evolved Packet System (EPS) bearer (or simply bearer in short).

When an active UE moves across a base station boundary, its connections will be handed off to the new base station. There are several different types of handoffs: handoffs that require the bearer to be handled by a new S-GW, a new MME, or handoffs that require the change of radio frequency or radio technology (e.g. from LTE to 3G). Some of these procedures are very involved. For an active UE, the network knows its current associated base station. For an idle UE, the network knows its current tracking area. A tracking area is a set of base stations that are geographically nearby.

S-GWs are mainly used as mobility anchors to provide seamless mobility. P-GW centralizes most network functions like content filter, firewalls, lawful intercepts, etc. P-GWs sit at the boundary of the cellular networks and the Internet. A typical LTE network can cover a very large geographic area and can have a pool of MMEs, S-GWs and P-GWs for reliability and load balancing purposes.

From a UE's perspective, LTE network protocols consist of protocols between the UE and MME, and between the UE and the base station. When a UE powers up, it initiates the attach procedure with MME. When a UE has data to send, it initiates a service request with the MME. These procedures trigger the radio resource control (RRC) connection setup procedure which involves several message exchanges with the base station. When the network has data to send to a UE when it is idle, a paging procedure is invoked.

2.2 Data Collection

Due to the sheer traffic volume, LTE networks do not continuously collect packet traces[2]. LTE networks continuously collect the following types of data.

Bearer and signaling procedure records A UE communicates with the network by establishing one or more bearers. Each bearer may have a different QoS profile or connect to a different IP network. Multiple TCP connections can be carried in one bearer. LTE networks keep track of a rich set of bearer statistics at the procedure level, like (1) transmitted and retransmitted bytes in the RLC sublayer of the data link layer, (2) number of transmissions and retransmissions in the MAC sublayer of the data link layer, (3) physical radio resources allocated, radio channel quality known as CQI, in the physical layer, (4) bearer success or failure reasons, (5) associated base station, S-GW, P-GW, MME, (6) bearer start and end time. LTE networks also collect data on many signaling procedures such as initial attach request, service request, handoff, paging (wake up a UE to receive incoming traffic). Data is collected at MMEs and base stations and is organized as records. Each record can have *several hundred* fields. In a LTE network, there is a pool of MMEs, S-GWs and P-GWs. A base station can communicate with multiple MMEs. Hence bearer level records need to be merged across MMEs.

Network element records Network elements such as base stations, MMEs have operational statistics such as aggregate downlink frame transmitted per time window and number of bearers failed per time window. These records are collected continuously. Data accumulated for each time window are sent to the operation center. Cellular analytics systems [3, 4, 10] at these centers use the data and configuration information of network elements and subscriber profiles for network monitoring, troubleshooting, trending analysis, planning and network optimization.

Figure 2 shows the number of active daily users and the amount of RLC layer traffic per hour during the peak hours from 4PM to 8PM in a typical week in the network we study. We define active

[2]Packets may be collected for a duration to enable fine-grained troubleshooting.

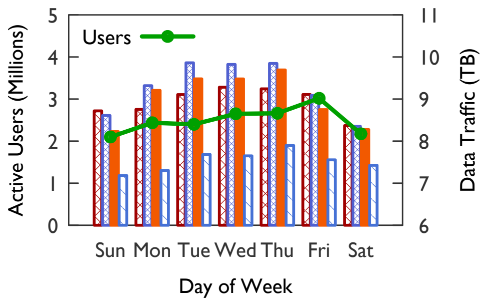

Figure 2: Active users and RLC layer traffic volume per peak hour (4PM to 8PM). Each bar represents the average for one peak hour.

users as those who used the network at least once in a given day. The portion of the network we studied serves over 2 million active subscribers using over 14,000 base stations, each with multiple cells. The volume is more than 6 TB per hour. We collected data for over a year, resulting in several 100s of TB of data.

2.3 RAN Performance Troubleshooting

Operators monitor a large number of KPIs per cell or per cluster of cells. These KPIs are classified into:

- *Accessibility.* Captures how available the RAN is. Includes attach and RRC connection failure rates.
- *Retainability.* Captures how well the network can complete the connection. It includes total bearer drop rate.
- Uplink and downlink *physical layer throughput.*
- *Quality.* Downlink & uplink block error rate (BLER).
- *Traffic volume.* Captures the uplink and downlink radio link layer traffic volume.
- *Connected user counts.* This include average RRC connected users and maximum RRC connected users.
- *Mobility.* Includes failure rates of various handoff types, tracking area update failure rate and paging success rate.

Existing practice, adopted by most major cellular network operators, is to use performance counters to derive these KPIs. The derived KPIs are then monitored by domain experts, aggregated over certain pre-defined time window. Based on domain knowledge and operational experience, these KPIs have service level agreements (SLA) to meet. For instance, an operator may have designed the network to have no more than 0.5% call drops in a 10 minute window. When a KPI that is being monitored crosses the threshold, an alarm is raised and a ticket created. This ticket is then handled by experts who investigate the cause of the problem. Our conversation with the network administrators revealed that such investigations can extend for several months, and may require expensive field trials. We have also confirmed with the experts that many of such alarms have known causes, but it is not possible to quickly conclude so due of the use of aggregated counters in deriving the KPIs.

3 METHODOLOGY

Our work focuses on access network problems. While there are other factors that affect application performance (e.g., poor interaction of the network with TCP [14] and buffer bloat [16]), they are orthogonal to our work since they do not originate in the RAN. Access network problems are among the hardest to diagnose because of the inherent nature of wireless networks; it is hard to capture the intricate details of the numerous procedures in an LTE network.

The path towards problem diagnosis starts with detecting whether a problem exists. This can be done in two ways: *passively*, where the operator comes to realize the problem when affected end-users report them, or *actively*, where the operator continuously monitors the network for problem detection before they become worse. Since passive approaches significantly degrade user experience, most cellular network operators actively monitor their networks. For this purpose, they define and monitor a number of performance metrics, which are termed Key Performance Indicators (KPI). We focus on access network KPIs for the rest of this paper.

3.1 Problem Isolation to RAN

Our quality of user experience can be impacted by many factors in the client side, cellular network and the Internet server side. The first step in analyzing performance issues is to isolate problems related to the access network. We achieve this by eliminating known non-RAN problems and modeling exogenous factors as noise.

Problems in the core network will impact a large number base stations. For example, if the Serving Gateway (S-GW) is overloaded, all base stations communicating with the S-GW will be impacted. Similarly, if a router in the core network has problems, it will impact all base stations that route through it. Although not common, core network problems do occur [9]. For example, we found a case where AS prepending was not configured properly, and caused reachability problem which impacted many base stations. However, due to their larger footprint, core network problems are relatively easy to detect.

Problems in the client side can also adversely impact access network KPIs. During conversations with network experts, we learned that there were cases where known phone models caused significant degradation of access network KPIs. We model other exogenous factors at the client side, Internet and server side as the noise impacting access network KPIs. These factors typically do not contribute to the KPIs problems of a large number of cells. However, they may be the main factor for a small number of cells. For example, if many users attached to a cell access the same overloaded server, then the throughput KPI will be adversely impacted.

Manually isolating the problem to RAN is cumbersome and infeasible to scale. Fortunately, there already exists a system for problem reporting and resolution, albeit manual, in the form of trouble tickets. We leverage this ticket system to automatically isolate problems to RAN. For instance, when a problem is detected, we can make sure that there are no core network problems by checking the ticket system. Similarly, we can ensure there is no significant correlation between KPI degradation to avoid device specific problems. We further use years of ticket resolution history and expertise of the network operator to form filtering rules.

3.2 Classification of RAN Problems

In the second step, we classify the access network problems, obtained as described earlier, into different categories. Classifying them into broad bins lets us analyze *classes* of problems rather than *individual* issues. In addition to letting us focus on the important problems, this also helps us with our goal of developing diagnosis methods that can be automated. We broadly classify problems into

LTE Physical Layer Parameters	
Name	*Description*
RSRP	Reference Signal Received Power: Average of reference signal power (in watts) across a specified bandwidth. Used for cell selection and handoff.
RSRQ	Reference Signal Received Quality: Indicator of interference experienced by the UE. Derived from RSRP and interference metrics.
CQI	Channel Quality Indicator: Carries information on how good/bad communication channel quality is.
SINR	Signal to Interference plus Noise Ratio: The ratio of the power of the signal to the interference power and background noise.
BLER	Block Error Ratio/Rate: Ratio of the number of erroneous blocks received to the total blocks sent.
PRB	Physical Resource Block: The specific number of subcarriers allocated for a predetermined amount of time for a user.

Table 1: A description of key parameters in LTE physical layer

the following, in the order of importance, based on our discussions with domain experts:

Coverage: Coverage represents one of the worst problems. Poor coverage can even lead to network inaccessibility, which often frustrates users. Unfortunately, such issues are hard to diagnose because traces cannot be generated when there is absolutely no coverage. However, it is possible to obtain insights on problems related to *poor* coverage using physical layer measurements. The primary physical layer parameter that influences coverage is RSRP (table 1).

Interference: Another major factor impacting user experience is interference. A user can be in an area with great coverage but still not be able to use the network due to the interference from nearby cells and/or users. This is especially true in LTE networks which is fundamentally designed for channel reuse. The amount of interference is influenced by the physical layer parameters RSRQ, CQI and SINR (table 1).

Congestion: While coverage and interference are characteristics of the user location, other factors also affect end-user experience. For instance, a base station can be overloaded. Congestion impacts many access network KPIs.

Configuration: Base stations have hundreds of configuration parameters, many of which are created and managed manually. It is easy to envision errors in these configurations, leading to many problems. For example, incorrect neighbor list or PCI configuration can adversely affect KPIs.

Network State Changes: Operators frequently update their networks (e.g., new releases and/or features). During the upgrades, problems can occur due to conflicts in software and/or because of compatibility issues.

Others: Software bugs, protocol implementation problems and hardware malfunction are some of the many other reasons for problems occurring in the RAN.

3.3 Root Cause Diagnosis

In the third step, we diagnose the root cause for these problems.

3.3.1 ***Issues with Cell-Level Metrics***. Existing RAN troubleshooting techniques are based on *cell-level* metrics. Specifically, these methods build cell-level KPIs using aggregated counters. For example, the operator may create the RSRP histogram for each cell in each time window (e.g., every 10 minutes). Unfortunately, aggregating information at the cell-level results in major shortcomings due to its coarse-grained nature. Not only does aggregation result in many problems not being detected, the mixing of several bearers' RSRP in the aggregate counter makes it impossible to identify the impact of root causes in detected problems.

3.3.2 ***Modeling Bearer-Level Metrics***. Our approach is to *model* performance metrics at the *bearer-level* using physical and MAC layer parameters. The use of bearer-level metrics eliminates the problems with cell-level metrics; and having a model lets us explain *why* things happened, thus diagnosing the problem. Our diagnosis methodology starts with eliminating known root causes, such as call admission control failures. Based on the classification of RAN problems, we distinguish two types of performance metrics:

Event Metrics: Several of the key performance metrics in RAN are discrete events. For instance, failures and drops are based on binary outcome. These metrics present a natural fit for models based on classification models, hence we use them. In particular, we describe a model for call drops using decision trees in §4.1.

Non-event/Volume Metrics: For continuous variables such as bearer throughput, we use the underlying information-theory model. §4.2 describes a regression model to diagnose throughput problems.

We describe the bearer-level modeling in detail in the next section. While our models are based on bearer-level, it may be useful to analyze problems at the cell level. For instance, the operator may wish to isolate cells that are consistently bad, or compare cells for troubleshooting. Our bearer-level approach makes this easy to do.

3.3.3 ***Computing Cell-Level Models***. Given a bearer-level model, $Y = f(X)$, we can compute the cell-level model. We have two cases. First, Y is an event-based metric, e.g., RRC failure. The cell-level failure rate Z for time window j can be modeled as:

$$z_j = \frac{1}{N_j}\sum_{i=1}^{N_j} y_i = \frac{1}{N_j}\sum_{i=1}^{N_j} f(x_i) \tag{1}$$

N_j is the number of bearers that start in time window j. z_j is estimated failure rate in time window j. If X is RSRP, then f is a multi-step function. If we only have RSRP histogram information (and not bearer-level information) in time window j, it will be very hard to model fit the histogram with failure rate.

Second, Y is a transmission-based metric, e.g., bearer throughput. The cell-level aggregate throughput Z at time window j is:

$$z_j = \frac{1}{T_j}\sum_{i=1}^{N_j} y_i \times \tau_i = \frac{1}{T_j}\sum_{i=1}^{N_j} f(x_i)\tau_i \tag{2}$$

T_j is the total non-idle time of the cell and N_j is the number of bearers fall into time window j. τ_i is the fraction of scheduled time that is in time window j.

Comparing Cell-Level Models: If all the cells in the network are identical, the model we derive is equivalent to a per-RAN model that will apply across all cells. However, performance characteristic vary across cells. For example, we have learned that different cells may configure different number of retries in the random access procedure. Intuitively, for the same RSRP, a cell with a high number of retries will lead to fewer RRC failures and vice-versa. Our methodology can accommodate clustering cells based on their

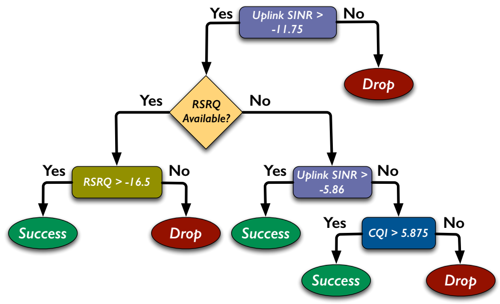

Figure 3: A sample decision tree used to explain drops. A random forest might provide better accuracy, but understanding the reason behind the drop is crucial for operators.

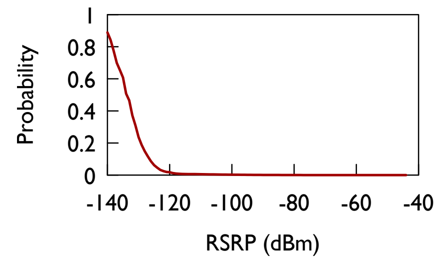

Figure 4: Impact of coverage on connection drops

model similarity (§5). This helps in comparing these clusters in terms of configuration parameters and base station capabilities.

4 BEARER-LEVEL MODELING

In this section, we discuss bearer-level modeling in detail using two key bearer performance metrics, *connection drops* and *throughput*. These represent the two types of metrics our work aims to model. To build models for each of these metrics, we leverage protocol details in the physical, link and MAC layers.

4.1 Connection Drops Model

One of the core performance metrics for the cellular network operator is *retainability*, which captures how well the network can complete the connection. The retainability KPI is affected by RRC connection drop events, and are thus crucial for end-user QoE. Our traces give us ground truth (they indicate drops, but not the reason).

For certain drop events, we have known root causes recorded in the data, e.g., call admission control failure or access denied. We filter these out. This pre-processing step helps us avoid false alarms during troubleshooting. For example, one ticket showed that the connection failure KPI degradation of one cell was actually due to an unauthorized UE repeatedly trying to access the network. Note that the network can not block a UE from trying to access it because the UE can make an emergency call without subscription.

4.1.1 ***Decision Trees for Modeling Event Metrics.*** Due to the intricate nature of the wireless medium, connection drops are influenced by a combination of the underlying layer parameters instead of any single one. Such a setting, along with the availability of tremendous amounts of data lends itself a good fit for machine learning (ML) techniques [18]. Since we are interested in event metrics, we leverage classification techniques in ML.

In particular, we use decision trees to model event metrics. While there are several other, more sophisticated, techniques such as random forests [12], our primary goal is to obtain a model that can *reason* about the model decision. A decision tree is simple to understand, and directly provides us the underlying reason for a classification it makes. We use the collected data to train supervised decision trees (since we know the ground truth). The features for the learning are all those that fall into our broad categories. We also leverage domain knowledge for feature engineering. For instance, connection drops are affected directly by uplink and downlink channel conditions. Decoding probability depends on SINR. Hence we consider uplink and downlink SINR, which are available as raw features in the data. For downlink, we convert raw CQI to engineered feature, SINR.

An example of a learned decision tree is shown in fig. 3. As we can see, it first classifies based on uplink SINR, and then makes use of RSRQ if available. Otherwise, it uses uplink SINR and CQI. Experts confirm that the model agrees with their manual, labor intensive troubleshooting experience. In many of this network's cells, connection drops are mainly due to interference. Uplink SINR is more unpredictable because the interference comes from subscribers associated with neighboring base stations. In contrast, downlink interference is from neighboring base stations. This model achieved an accuracy of 92.1% with a cross-validation error of 10.1%.

4.1.2 ***Findings from Per-Root Cause Analysis.*** We were surprised by the decision tree models built by our approach, such as the one depicted in fig. 3, for many cells in this operator's network. Intuitively, we would have associated connection drops with poor coverage (RSRP). However, the model ignored RSRP and picked interference instead as the primary reason for drops. In addition, the model distinguishes between downlink RSRQ and CQI, which should affect interference similarly in theory.

To understand why our approach built this model, we studied the impact of each underlying root-cause (§3.2) *individually*. We plot the probability distribution of connection drops against physical layer parameters. This resulted in interesting insights.

Coverage Physical layer parameter RSRP is the received signal power of reference signals from the base station which can act as an indication of coverage. We plot the emperical distribution of connection drop with respect to RSRP in fig. 4. Areas with $RSRP < -130$ dBm experience high drops, but are relatively less in number.

Uplink Interference As shown in fig. 5, the drop probability for uplink SINR has a rather steep slope and peaks at -17dB. This is because the scheduler stops allocating grants at this threshold. If conditions do not improve, the connection will be dropped.

Downlink Interference There are two metrics to consider: RSRQ and downlink CQI. RSRQ is only reported when the UE might need to handoff. CQI is available independent of handoffs. Under normal circumstances, they should have identical shape. But from fig. 6 and fig. 7, we see that is not the case. To reveal the difference of these two distribution, we converted them to a common base, SINR. To convert CQI, we just use the standard CQI to SINR table. To convert RSRQ, we use the formula derived in [22], $SINR = \frac{1}{\frac{1}{12RSRQ} - \rho}$, where ρ depends on subcarrier utilization. For two antennas, it is between 1/3 and 5/3. For connection failure cases, we show the emperical distribution of their SINR differences with

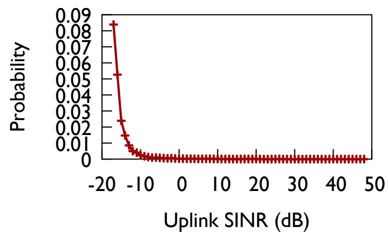

Figure 5: Impact of UL SINR on drops

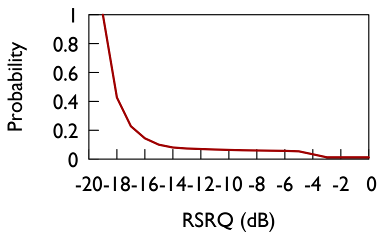

Figure 6: Impact of DL RSRQ on drops

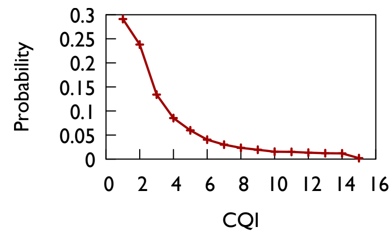

Figure 7: Impact of DL CQI on drops

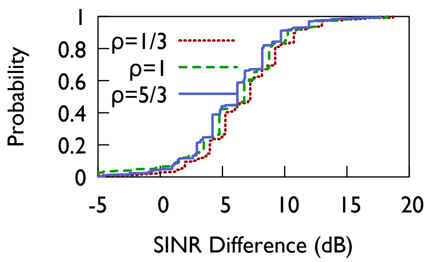

Figure 8: SINR gap between CQI and RSRQ

0%, 50% and 100% subcarrier utilization in fig. 8. We see that 10% has a SINR difference of 10 dB. This large discrepancy cannot be explained by hardware dependency or channel variations during our averaging time window.

Finding Insight: After talking to experts, we learned that P-CQI feedbacks through physical uplink control channel are not CRC protected. Correct decoding requires setting a threshold for received signal strengths under different channel conditions. It seems that the adaptation is problematic sometimes. P-CQI passing detection threshold can not be decoded correctly. Since there is no CRC, some spurious P-CQI will be used by the physical layer link adaption algorithm. This can cause high BLER leading to connection drops.

4.2 Throughput Model

RLC layer throughput is another important KPI in RAN.

4.2.1 ***Regression for Modeling Volume Metrics.*** Since volume / non-event metrics are continuous values, regression techniques in machine learning provides an attractive option to use to build diagnostic models. Regression models can output continuous values, and thus can be used to *predict* volume metrics based on input features. For instance, we can form an information-theoretic regression model that predicts throughput based on metrics. Our traces report the transmitted and retransmitted bits, and the total transmission time per bearer at the RLC sub-layer. Thus, we know the RLC throughput as the ground truth. When the predicted values and the actual values match (when the model is accurate), the regression model provides us the reasoning, in the form of weights on the input features, for why a particular throughput was achieved.

However, building an information-theoretic model is non-trivial because we need to account for the overhead in different layers (e.g., physical layer control channel overhead, MAC layer retransmission overhead). We again leverage domain knowledge and feature engineering to obtain a model for throughput prediction:

SINR Estimation Base stations have two antennas capable of MIMO spatial multiplexing (two streams) or transmit diversity. For both type of transmissions, each UE reports its two wideband CQIs, one per antenna. We use the CQI to SINR mapping table used at the base station scheduler to convert CQI to SINR. For transmission diversity, we convert the two CQIs to a single SINR: First we convert both CQIs to SINR, then we compute the two spectrum efficiencies (bits/sec/Hz) using Shannon capacity. We average the two spectrum efficiencies and convert it back to SINR. We then add a 3dB transmission diversity gain to achieve the final SINR. For spatial multiplexing, we convert the two CQIs to SINRs.

Account for PRB Control Overhead and BLER Target Each PRB is 180 KHz, but not all of it is used for transmission. For transmit diversity, a 29% overhead for each PRB exists on average because of resources allocated to physical downlink control channel, physical broadcast channel and reference signals. The physical layer has a BLER target of 10%.

Account for MAC Sub-layer Retransmissions The MAC sublayer performs retransmissions. We denote the MAC efficiency as β_{MAC}. It is computed as the ratio of total first transmissions over total transmissions. We compute β_{MAC} using our traces. The predicted throughput due to transmit diversity is calculated as:

$$\begin{aligned} tput_{RLCdiv} &= (1.0 - \beta_{MAC}) \times 0.9 \times (1 - 0.29) \times 180 \times \\ &\quad PRB_{div} \times log2(1 + SINR_{div}) / TxTime_{div} \end{aligned}$$

PRB_{div} denotes the total PRBs allocated for transmit diversity. $TxTime_{div}$ is the total transmission time for transmit diversity. Similarly we can calculate the predicted throughput due to spatial multiplexing. We then properly weigh the two by their respective fraction of transmission time to derive the final RLC throughput.

Account for Link Adaptation The base station does not use the SINR corresponding to the UE reported CQI directly. It performs link adaptation to achieve the desired BLER of 10%. If the observed BLER is higher than target, it will adjust the SINR by subtracting a few dB. If the observed BLER is lower than the target, it will adjust the SINR by adding a few dB. To increase the speed of converging to the BLER target, the feedback offset is computed differently according to deviation to the target BLER. For large deviations, the large step power offset is applied so that BLER can converge faster to the long term adaptation area. This adaptation is necessary since the propagation channel is subject to several conditions that vary in space and time, e.g., path loss, fast fading, UE speed and location. Since the base station adjusts a maximum of 6dB, we adjust the SINR used in our prediction by -6dB to compute the lower bound and +6dB to compute the upper bound. We compute the prediction error as follows. If the actual throughput is within the two bounds,

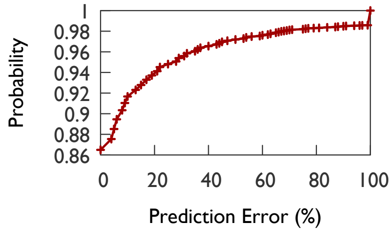

Figure 9: Actual vs predicted throughput

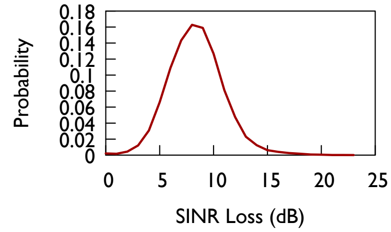

Figure 10: Loss of efficiency (dB)

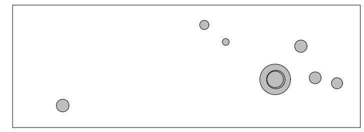

Figure 11: Geographic location (not to scale) of cells by aggregated dB loss shows losses are concentrated on a few cells.

the error is zero. Otherwise, the error is the distance to the closest bounds. The CDF in fig. 9 shows that our model is very accurate.

*4.2.2 **Finding: Loss of Efficiency**.* We characterized the difference between predicted throughput and actual throughput in terms of loss in dB. To compute this, we first convert the actual throughput into SINR. We then substract the SINR from the one used for throughput prediction. Figure 10 shows the distribution. It has a peak around 8dB. As we can see, around 20% of the bearers have a loss of efficiency of more than 10 dB.

To obtain insights on these high losses, we analyzed them aggregated by the cell in which the loss was experienced. Figure 11 presents the results of this analysis. For the purpose of anonymity, we do not provide the actual location of the cell, but only show the relative locations scaled by a constant factor. We find that a few cells contribute to many of the losses. Further, two cells from the same base station contribute to as much as 5 times the losses experienced by any single cell (including cells not shown).

We further investigated if the loss is a characteristic of the user. The first question is whether these losses are experienced by the same user. We find that this is not the case. While users tend to experience the loss continuously as long as they are in a cell and are actively utilizing the network, the aggregate loss is contributed by many users. A second suspect is the device model. Different manufacturers use different radio chipsets, and hence the measurements made by the device may differ. We find that most of the losses occur in Apple iPhones. But they are also the most used devices in our network, so we do not conclude that model contributes to losses.

Finding Insight: Due to the high fraction of bearers with high dB loss, we posit that the link adaptation algorithm is slow to adapt to changing conditions. We validate this based on two evidences. First, the link adaptation algorithm uses moving average SINR, which is a slow mechanism to adapt. Second, field experts confirmed our observations by replicating them in lab tests.

4.3 Detecting False Positives of KPI Changes

Our models can significantly reduce operator's troubleshooting efforts. For instance, it can help remove false positives of significant cell level KPI changes. We show this using drop rate. To do so, we apply the decision tree in §4.1 on a week worth of data divided into 10 minute windows. We used this window length since it matches closely with an interval that is usually used by the operators for monitoring drop rates. In every window, we predict the number of drops using our technique. The predicted drops are explainable, because we know precisely why those drops happened. We use a threshold of 0.5% for the drop rate (operator's SLA), hence anything

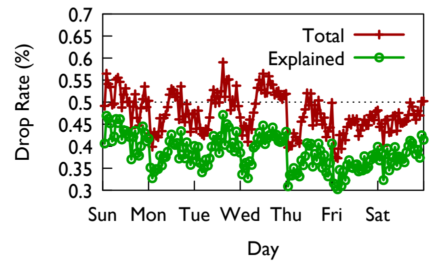

Figure 12: Our method can detect false positives in alarms, thus relieving the operator from re-investigating known problems.

above this threshold is marked as an anomaly. The results from this experiment is depicted in fig. 12. At numerous places the threshold is exceeded. Normally, these would have to be investigated by an expert but more than 80% of the drops are explained by our model.

To estimate the confidence, we analyzed our prediction results during the occurrence of these anomalies. We consider each connection drop or complete event as a Bernoulli random variable X with probability p (from decision tree). A sequence of n connection events follow a binomial distribution. The 95% confidence interval is approximated by $np \pm 2\sqrt{np(1-p)}$. We determine that the alarm is false if X is within the confidence interval. The bound was found to be (0.7958665, 0.8610155), which is within acceptable range.

4.4 Summary

To summarize our approach, we began by isolating problems to the RAN by leveraging the operator's existing ticket resolution system to filter our non-RAN related problems. We then classified problems into broad categories based on underlying root causes, each of which could be influenced by physical or mac layer parameters. Then we proposed building bearer-level models for key performance metrics for root cause diagnosis. For event metrics, we build decision tree models and for volume metrics we build information-theoretic regression models, in both leveraging domain knowledge for feature engineering. These models helped us unearth interesting insights. Finally, we show how the operator could leverage these models to reduce troubleshooting efforts.

5 DISCUSSION & FUTURE WORK

In this work, we discussed how using fine-grained, bearer level information could be beneficial in diagnosing performance problems in RANs. Based on this, we proposed models for RAN diagnostics that are amenable to automation. During the course of this work, we learned several valuable lessons and future work opportunities.

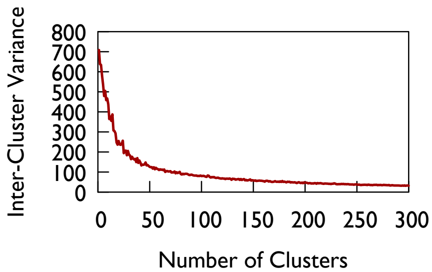

Figure 13: Number of clusters are small even when the number of cells are large (>50k).

First, fully automating diagnostics requires building models for several categories of metrics. Due to the large number of base stations in a RAN, this results in several thousands of models. Building and managing them can easily be a bottleneck, and requires engineering efforts to scale as generating models are compute-intensive. We plan on leveraging advancements in big-data machine learning.

Second, we found that due to the spatio-temporal nature of the wireless medium, the performance characteristics and thus the accuracy of the models are also highly spatio-temporal. This means that the automation system should be able to update the models it builds periodically. Unfortunately, this is not just a scalability challenge. Since failures are rare in a relative sense, building *effective and accurate* models is a research challenge. In our current system, we rebuild the models manually, which is not ideal.

We have made some progress towards these challenges. Specifically, we found that cells exhibit performance similarity. If we build a model $Y = f(X)$ for performance metric Y in terms of root cause X, we can order the predicted Y values as a vector and then use the vector distance between cells in a K-mean clustering algorithm. Figure 13 shows the variance between clusters with varying number of K. We see that the number of clusters can be small even with a large number of cells (>50k in our case). As an example, clustering on uplink SINR shows just 10 dominant clusters (fig. 14). The difference of clusters can be due to different base station releases (thus may have different algorithms e.g., link adaptation), different hardware capability (e.g., receiver sensitivity), the number of retries configured in the random access procedure. This indicates that it may be possible to use a single model for a group of cells.

Finally, with the industry moving towards software-defined cellular networks [1, 2], network operators must be able to support RAN performance diagnostics in *real-time*. The methodology we discussed here has the potential to be a real-time solution, and can even go further by predicting *potential future problems* because of its use of models. An open research challenge is in building and updating the models in real-time in a scalable fashion. We plan on leveraging learnings from our work on real-time analytics on cellular networks [15] for addressing some of these challenges.

6 RELATED WORK

Cellular Network Monitoring and Troubleshooting A number of cellular network monitoring and diagnosis systems exist [3–5, 8, 11]. AT&T GigaScope [8] and Alcatel-Lucent Wireless Network Guardian (WNG) [3] generates per IP flow records and monitors many performance metrics such as aggregate per-cell TCP throughput, delay and loss. Because these tools tap interfaces in the core networks, they lack information at the RAN. Systems targeting RAN [4, 11] typically monitor aggregate KPIs and per-bearer records separately. Their root cause analysis of KPI problems correlates with aggregation air interface metrics such as SINR histograms and configuration data. Since they rely on aggregates, it is hard for them to provide fine-grained diagnosis. Several studies [6, 14, 16, 19, 21, 26] focus on the interaction between applications and cellular networks. They are orthogonal to our work.

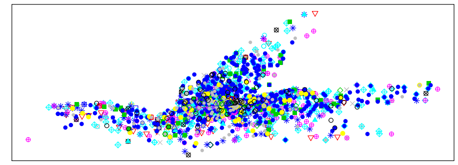

Figure 14: Geographic locations of cells clustered by model (color) shows they share performance characteristics (best viewed in color).

Modeling and Diagnosis Techniques Diagnosing problems in cellular networks has been explored in the literature in various forms [7, 13, 17, 20, 25], where the focus has either been detecting faults or finding the root cause of specific failures. A probabilistic system for auto-diagnosing faults in RAN is presented in [7]. It relies on KPIs. However, KPIs are not capable of providing diagnosis at high granularity. Moreover, it is unclear how their proposals capture complex dependencies between different components in RAN. An automated approach to locating anomalous events on hierarchical operational networks was proposed in [13] based on hierarchical heavy hitter based anomaly detection. It is unclear how their proposals carry over to RAN. Adding autonomous capabilities to alarm based fault detection is discussed in [17]. While their techniques can help systems auto-heal faults, correlation based fault detection is insufficient for fine granularity detection and diagnosis of faults. [20] looks at detecting call connection faults due to load imbalances. In [27], a technique to detect and localize anomalies from an ISP point of view is proposed. Finally, [25] uses machine learning to predict impending call drops and duration.

7 CONCLUSION

In this paper, we share our experience working with a major cellular network operator in answering the question of whether it is possible to develop automated solutions for problem detection and diagnosis in RANs. We show that fine-grained analysis is the key, and propose a bearer-level modeling methodology for RAN diagnostics. During this process, we were able to unearth several insights from the operator's RAN, some previously unknown. We learned that automatic detection and diagnosis of RAN problems in real-time requires answering several research challenges. We are currently pursuing many of them.

ACKNOWLEDGMENTS

We would like to thank the Mobicom reviewers and our shepherd, Chunyi Peng, for their valuable feedback. This research is supported in part by DHS Award HSHQDC-16-3-00083, NSF CISE Expeditions Award CCF-1139158, and gifts from Ant Financial, Amazon Web Services, CapitalOne, Ericsson, GE, Google, Huawei, Intel, IBM, Microsoft and VMware.

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