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Quantifying the Impact of Base Station Metrics on LTE Resource Block Prediction Accuracy

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***Abstract*—Accurate prediction of cellular link performance represents a corner stone for many adaptive applications, such as video streaming. State-of-the-art solutions focus on distributed device-based methods relying on historic throughput and PHY metrics obtained through device APIs. In this paper, we study the impact of centralised solutions that integrate information collected from other network nodes. Specifically, we develop and compare machine learning inference engines for both distributed and centralised approaches to predict the LTE physical resource blocks using ns3-simulation. Our results illustrate that network load represents the most important feature in the centralised approaches resulting in halving the RB prediction error to 14% in comparison to 28% for the distributed case.**

***Index Terms*—cellular network, machine learning, physical resource blocks, LTE, 4G**

I. Introduction

Cellular networks represent a challenging environment for delay and bandwidth-constrained applications. Typically, the base station (BS) scheduler allocates wireless resources based on the past allocated throughput and their channel conditions. This design intends to balance achievable network throughput and ensure user fairness [1]. Considering the highly variable dynamics of the radio channels and cell load in cellular systems, the allocated resources could dramatically change over time. These changes represent a challenge for various adaptive applications, such as video and AR/VR. Hence, the ability to predict future resource allocation becomes of paramount importance to such throughout and latency-sensitive applications.

State-of-the-art solutions employ machine learning (ML) to predict future link performance in a distributed fashion. These solutions rely on data collected from the end device including historic throughput, PHY parameters (e.g., CQI, RSRP, RSRQ,..), and other context parameters. The distributed approach has many limitations. First, the device has no access to important information, such as network load and other users' states. Additionally, the availability and granularity of model features could be limited by different factors, such as the API design. For example, update of PHY metrics in Android devices has course granularity (1-sec) [2]. Hence, the model accuracy in distributed solutions remains limited to the quality and nature of the available data.

In this paper, we investigate the impact of integrating scheduler data on the accuracy of Resource Block (RB) prediction. The BS receives periodic reports including device-specific PHY metrics from every connected device. Additionally, the scheduler is aware of the cell load, including the number of connected users. Hence, using a centralised (network-based) approach, we can consider all the available information at the BS scheduler. The contribution of our short paper is to quantify what impact the availability of this BS scheduler information has on the accuracy of allocated RB prediction. Our results show that it can reduce the 90% error by 10% in comparison to the distributed (device-based) solution.

II. Prediction of PHY Resource Blocks

A. Methodology

Our data is based on ns3 500-second simulations considering a seven-cell LTE topology with 60 mobile clients using the Gauss-Markov model with speed ranging from 0-60kmh. All users are initially randomly scattered across seven BSs. We fix the inter cell-site distance to 500 m and cell transmission power to 44 dBm. The path loss model is the 3GPP urban propagation loss model [3], and the carrier bandwidth is 10 MHz (50RBs). All users download UDP traffic at a fixed rate (i.e., 32Mbps). We split the data using 80%:20% for training and testing without shuffling. In particular, we take data from 48 users for training and use the remaining 12 user data for testing.

We developed ML models to predict the user allocated resources in the form of physical RBs. We employ random forest (RF) [4] as our ML algorithm as it outperforms other ML techniques for this problem space [5] and it requires minimal tuning (the number of trees is the most critical hyperparameter). We consider two key prediction approaches: the *device-based* and *network-based* scenarios. For the device-based approach, we consider PHY metrics available through Android APIs, shown in Table I. For the network-based approach, the considered metrics (shown in Table I) are available at the BS at a fine granularity of 2ms (our interest is in determining the achievable bounds, which would be affected should practical considerations mean that metrics are exposed at coarser granularity). In all the developed models, we use the values of the last five seconds as input (i.e., history duration equal to 5). For the output, we consider the average number of RBs assigned to the user for the next five seconds (i.e., horizon equal to 5)[1]. The collected data is used without any processing other than normalisation.

We compare the performance of the following scenarios:

- **SC1**: device-based scenario considers instantaneous feature values with 1-second sampling interval to match the aforementioned limits of Android API. Specifically, we use the last sample for every PHY metric in the monitoring period. This scenario represents a baseline scenario.
- **SC2**: device-based scenario assuming that the device API provides the average value of each feature instead of the instantaneous value every 1s. This case is considered to investigate the impact of feature representation through the device API on the inference accuracy.
- **SC3**: device-based scenario assuming that the device API provides the average value of each feature instead of the instantaneous value every 0.25s. This case is considered to investigate the impact of the device API update frequency on the inference accuracy.
- **SC4**: network-based model with features representing the average value over 1s.
- **SC5**: network-based model with features representing the average value over 0.25s.

We evaluate the performance of these models using the *absolute relative residual error* (ARE). ARE is the ratio of the absolute difference between the actual and predicted resource blocks to the actual average resource blocks.

TABLE I
FEATURES USED FOR DEVICE- AND NETWORK-BASED SCENARIOS

Device-based	Network-based
CQI, RSRP, RSRQ, SINR, THR	Device + CCQI, CRSRP, CSINR, CTHR, Load, Delay

B. Results

Fig. 1 illustrates the ARE boxplot for key considered scenarios with the whiskers representing the minimum and maximum values. For the baseline device-based scenario (SC1), the maximum ARE reaches 28% when predicting RB over a 5-second horizon. SC2 boxplot illustrates that providing the average value of considered features through the device API reduced all error quartiles and brings the maximum error down to 23%. SC3 boxplot shows that allowing frequent updates for the features through the device APIs does not significantly change the error distribution from SC2 (1s update frequency), except for slight reduction in the 3rd quartile and maximum error. Hence, device-based approaches would benefit more from modifying the feature representation in comparison to speeding up the frequency of updates.

SC4 box plot illustrates that network-based inference with 1s periodicity brings the maximum ARE to 13.7%, less than half the value attained by the the baseline device-based scenario. This result indicates that integrating network features significantly reduces the prediction error. Additionally, SC5 boxplot illustrates that shrinking the monitoring interval to 250ms improves the prediction accuracy with the maximum ARE dropping to 12%. Note that reducing the sampling interval increases the involved computation due to increasing the number of features.

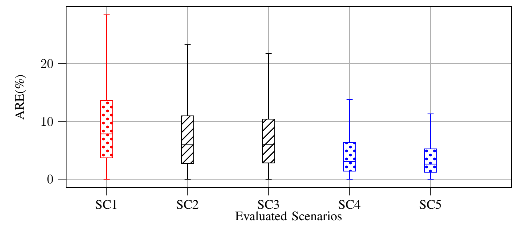

Fig. 1. Prediction accuracy for UDP traffic type under different scenarios (device-based and network-based), and data granularity (250ms and 1s)

The observed improvements are attributed to the importance of distinct network-based features. Most notably the cell load is of the highest importance, explaining 70% of the predicted RB value, followed by the past values of RB (13%), RSRP (3%), and competing RSRP (2.5%), and SINR (2.5%). For the baseline device-based scenario, the most important features are the past values of throughput, explaining 49% of the predicted RB value, followed by CQI (17%), RSRQ (16%), SINR (10%) and RSRP (8%).

III. Conclusion

In this paper, we analyse the prediction of resource allocation from device- and network-based features by applying ML techniques. Our results indicate that changing the representation and granularity of PHY metrics through device APIs would moderately enhance the inference of the allocated resources. Furthermore, network-based features significantly improve the inference accuracy for the allocated network resource. These findings can be leveraged to improve the performance of latency- or throughput-sensitive applications.

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