



Towards Cooperative Data Rate Prediction for Future Mobile and Vehicular 6G Networks

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Abstract—Machine learning-based data rate prediction is one of the key drivers for anticipatory mobile networking with applications such as dynamic Radio Access Technology (RAT) selection, opportunistic data transfer, and predictive caching. User Equipment (UE)-based prediction approaches that rely on passive measurements of network quality indicators have successfully been applied to forecast the throughput of vehicular data transmissions. However, the achievable prediction accuracy is limited as the UE is unaware of the current network load. To overcome this issue, we propose a cooperative data rate prediction approach which brings together knowledge from the client and network domains. In a real world proof-of-concept evaluation, we utilize the Software Defined Radio (SDR)-based control channel sniffer FALCON in order to mimic the behavior of a possible network-assisted information provisioning within future 6G networks. The results show that the proposed cooperative prediction approach is able to reduce the average prediction error by up to 30%. With respect to the ongoing standardization efforts regarding the implementation of intelligence for network management, we argue that future 6G networks should go beyond network-focused approaches and actively provide load information to the UEs in order to fuel pervasive machine learning and catalyze UE-based network optimization techniques.

I. INTRODUCTION

Although the concrete technological improvements of future 6G networks are still unclear, researches agree that data-driven intelligence will be a key driver for those novel networks which are expected to be deployed around 2030 [1]. As a consequence, the 3rd Generation Partnership Project (3GPP) is currently investigating data analytics-based networking as an enabler for network automation [2]. An example is the Network Data Analytics Function (NWDAF), which has been specified in [3] as a novel 5G core network function allowing Mobile Network Operators (MNOs) to monitor the load of network slices based on machine learning methods.

While the ongoing standardization efforts for 5G mainly target *network-side* intelligence, different studies have demonstrated that edge-based [4] and *UE-based* optimization is not only able to improve the end user experience, but also contributes to improving the intra-cell coexistence of different devices. *Anticipatory* communication [5] has emerged as a novel mobile networking paradigm that aims to optimize decision processes by taking context information into account. In this field, machine learning-based data rate prediction is a key enabler for different applications. It allows to choose the best network interface in multi-RAT systems [6], predictively cache streaming data [7], and increase the resource efficiency of Massive Machine-type Communications

(mMTC) through opportunistic data transfer [8]. Moreover, end-to-end prediction models themselves can serve as highly accurate performance analysis tools based on Data-driven Network Simulation (DDNS) [9] techniques. Therefore, the optimization of the achievable prediction accuracy is a crucial research task which directly affects the performance of these applications.

For moving vehicles, the prediction of the currently achievable end-to-end data rate is a challenging task. Different studies (see Sec. II) have shown that network quality information can serve as a meaningful indicator for throughput prediction. However, the main drawback of pure UE-based prediction approaches is their unawareness of the potentially available network resources and the traffic load related to other active users. In this paper, we explore the benefits of *cooperative* data rate prediction as a possible method deployed in future 6G networks where network load information could be announced via control or broadcast channels. An overview of the proposed approach and the research goals is illustrated in Fig. 1. We mimic such a system by combining mobile UE measurements with information about the cell-wide radio resource allocations which are revealed by analysis of Physical Downlink Control Channel (PDCCH) using the SDR-based Fast Analysis of LTE Control channels (FALCON) [10] sniffer.

The remainder of the paper is structured as follows. After discussing the related work in Sec. II, we present the proposed cooperative prediction approach in Sec. III. Afterward, the applied methodology for the proof-of-concept evaluation is introduced in Sec. IV and finally, the results of the real world performance analysis are presented and discussed in Sec. V.

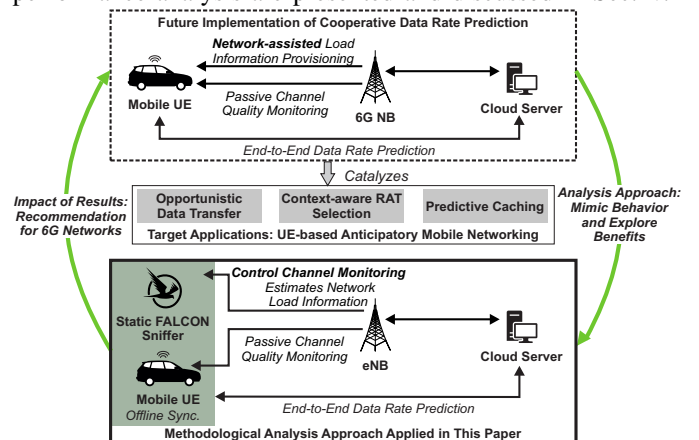


Fig. 1. Overview of the proposed cooperative data rate prediction approach.

TABLE I
CONTEXT DOMAINS OF EXISTING DATA RATE PREDICTION APPROACHES

| Study | Channel | Load | Mobility | Application |
|-------------------|---------|------|----------|-------------|
| Samba [11] | ● | ○ | ● | ○ |
| Jomrich [12] | ● | ● | ● | ○ |
| Wei [13] | ● | ○ | ● | ○ |
| Cainey [14] | ● | ● | ○ | ○ |
| Akselrod [15] | ● | ○ | ○ | ○ |
| Riihijarvi [16] | ● | ○ | ● | ○ |
| Sliwa [17] | ● | ● | ● | ● |
| Falkenberg [18] | ● | ● | ○ | ● |
| This paper | ● | ● | ● | ● |

● Full consideration, ● Partial consideration, ○ No consideration

II. RELATED WORK

Data rate prediction in vehicular networks is a highly challenging task due to the complex interdependency between mobility-, channel-, and network-dependent factors. As the resulting dimensionality of the problem is typically too complex for analytical approaches, machine learning models that implicitly consider hidden interdependencies between measurable variables are applied. A methodological summary of machine learning for wireless communications is provided by [19]. Data rate prediction can be considered as a *regression* task where *supervised* learning is applied to train a predictor f on measurement data \mathbf{X} labeled with ground truth values \mathbf{Y} such that $f : \mathbf{X} \rightarrow \mathbf{Y}$. After the training phase, the model can be utilized to make predictions $\hat{\mathbf{Y}}$ on unlabeled data. A distinction is made into *active* and *passive* prediction methods. While the former apply time series analysis on continuously monitored data rate measurements of ongoing transmissions, the latter only consider passively measurable signal quality indicators (e.g., the Signal-to-interference-plus-noise Ratio (SINR)) without any ongoing transmission. Since active approaches introduce additional traffic to the network, this paper focuses on the passive prediction approach which is also studied by the authors of [17], [11], [12], [13], [14], [15], [16]. The main conclusions of the previous studies are summarized as follows:

- All considered evaluations agree that passively measurable network quality indicators [20] are highly correlated to the data rate and can be used to forecast the achievable throughput.
- As discussed in [17], the prediction accuracy highly depends on the payload size of the to be transmitted data packet. Integrating the latter into the prediction process allows to implicitly consider effects such as the Transmission Control Protocol (TCP) slow start as well as cross-layer dependencies between the transport layer and the channel coherence time.
- In most evaluations (e.g., [17], [11], [12]), the highest prediction accuracy is achieved by Classification And Regression Tree (CART)-based models such as Random Forests (RFs). More complex methods like *deep learning* suffer from the limited amount of available training data.

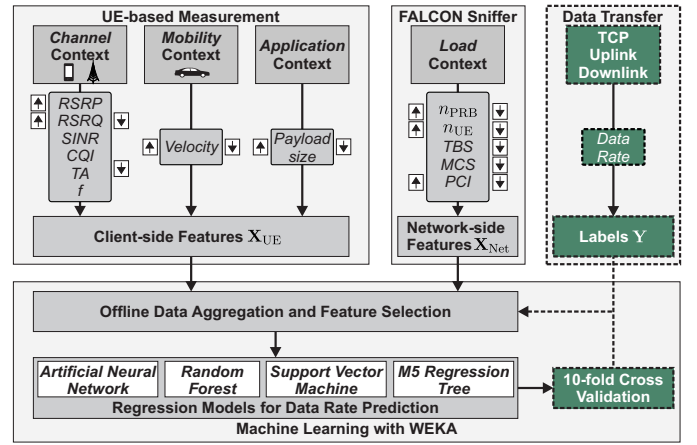


Fig. 2. System architecture model for the proposed cooperative data rate prediction approach. Relevant features after feature selection for up- and downlink are indicated by arrows \uparrow and \downarrow , respectively.

Control channel analysis is an accurate method for fine-grained monitoring of the overall cell activity, which is invisible to conventional UEs. In contrast to the mere observation of the spectral power density, which only provides a statement about the total utilization of available resources, the control channel analysis additionally breaks down the number of all competing subscribers as well as their individual throughputs. In terms of spectral radio resources, this enables a prediction of the *pie piece size* a new cell user shall expect for an intended transmission. In Long Term Evolution (LTE) networks, individual resource allocations for uplink and downlink, namely Downlink Control Information (DCI), are signaled via PDCCH to the UEs once per millisecond. Although this information is not encrypted, it is not readily accessible to an observer, since the integrity check presupposes knowledge of all Radio Network Temporary Identifiers (RNTIs) of currently active UEs. However, RNTIs are assigned only once during initial random access response and may take place prior to the observation period or even on a different component carrier in case of carrier aggregation. Therefore, real time cell monitoring requires advanced methods for discovery of missed RNTI assignments and reliable DCI validation techniques. To the best of our knowledge, FALCON [10] is currently the most accurate open source instrument for performing this task which reliably discloses currently active RNTIs and reveals all DCI from PDCCH. In order to not miss DCIs that are addressed to cell-center users and include less redundancy for error correction, the FALCON sniffer must be placed in proximity of the antenna of the monitored cell. Consequently, data rate predictions based on cell load, such as [18], are bound to stationary scenarios.

The motivation of this paper is to bring together stationary cell load information with measurements of mobile UEs, hence compensating the drawbacks of both approaches. As a result, a unique level of considered context domains is achieved and can be exploited for mobile data rate prediction. Tab. I summarizes the considered context domains exploited by related studies on the proposed cooperative approach.

III. COOPERATIVE DATA RATE PREDICTION

In this section, the proposed cooperative data rate prediction approach is presented. Based on the overall system architecture model shown in Fig. 2, the different components are explained.

Hybrid data acquisition: Different features for the machine learning process are captured by the mobile UE and the static FALCON sniffer. The mobile UE determines features from multiple context domains which are brought together in the client-side feature set \mathbf{X}_{UE} . These comprise

- **Channel context:** Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), SINR, Channel Quality Indicator (CQI), Timing Advance (TA) and the carrier frequency f ;
- **Mobility context:** Velocity of the vehicle;
- **Application context:** Payload size of the intended transmission.

In the training phase, the resulting throughput of each data transmissions is used as the label \mathbf{Y} for the prediction process.

In parallel, a statically deployed FALCON sniffer captures the cell's **load context** to derive network-side features \mathbf{X}_{Net} from the monitored resource allocations. These comprise, separated by up- and downlink, the statistics (i.e. average and standard deviation) of the number of active users n_{UE} , the number of assigned Physical Resource Blocks (PRBs) n_{PRB} , Modulation and Coding Scheme (MCS), and Transport Block Size (TBS), within a single subframe and within an observation window of 1 s. Based on synchronized timestamps, the data sets \mathbf{X}_{UE} and \mathbf{X}_{Net} aggregated offline for the training.

Feature selection: In order to maximize the information gain, redundancies related to highly correlated input variables are removed by an iterative feature selection for each transmission direction. The algorithm is initialized with an empty feature set $\mathbf{X} = \emptyset$ and a feature candidate set $\mathbf{C} = (\mathbf{X}_{\text{UE}} \cup \mathbf{X}_{\text{Net}}) \setminus \mathbf{X}$ of all remaining features. In each iteration, the performance R_i^2 (cf. Sec. IV-B, Eq. 1) is evaluated by including one additional feature $c_i \in \mathbf{C}$ for all $i \in [1, |\mathbf{C}|]$ and \mathbf{X} is appended by the best feature c_m with $m = \arg \max_{i \in [1, |\mathbf{C}|]} (R_i^2)$. The algorithm terminates as the prediction performance R_i^2 decreases or $\mathbf{C} = \emptyset$. For a feature set of length $n = |\mathbf{C}|$, up to $\frac{n(n-1)}{2}$ models are trained and evaluated. In Fig. 2, the features selected by the algorithm for up- and downlink data rate prediction are indicated by arrows \uparrow and \downarrow , respectively.

Machine learning models: The actual prediction is carried out with multiple supervised machine learning models. Parameters are chosen based on grid search in a preprocessing step.

- **Artificial Neural Network (ANN)** [21] with two hidden layers consisting 15 nodes, momentum $\alpha = 0.001$, learning rate $\eta = 0.1$ and 500 epochs.
- CART methods **Random Forest (RF)** [22] with 100 random trees and **M5 Regression Tree (M5)** [23].
- **Support Vector Machine (SVM)** [24] with Radial Basis Function (RBF) kernel which is trained with Sequential Minimal Optimization (SMO).

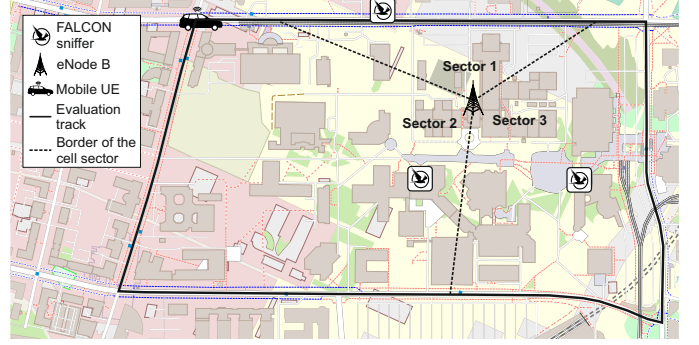


Fig. 3. Trajectory of the drive tests in a campus region including a serving cell with three sectors and locations of the associated FALCON sniffers (Map data: ©OpenStreetMap contributors, CC BY-SA).

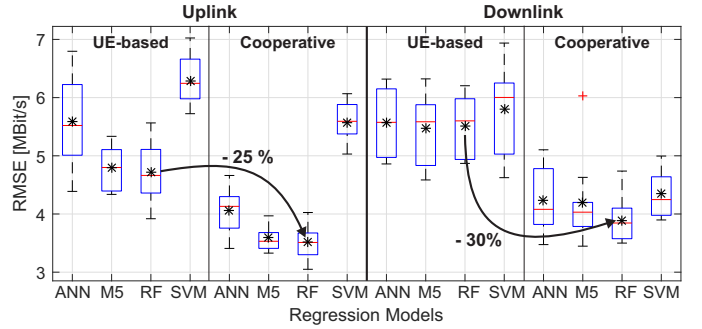


Fig. 4. Comparison of the resulting predictions errors of UE-based and cooperative data rate prediction for the considered machine learning models: Artificial Neural Network (ANN), M5 Regression Tree (M5), Random Forest (RF), and Support Vector Machine (SVM). The UE-based approach uses the full client-side feature set \mathbf{X}_{UE} .

IV. METHODOLOGY

This section provides an introduction of the methodological setup for the real world data acquisition and the machine learning-based data analysis.

A. Real World Data Acquisition

For the proof-of-concept evaluation, drive tests with data transmissions are carried out in a campus region that is covered by three sectors of a single evolved Node B (eNB) that belongs to a public LTE network as shown in Fig. 3. The mobile channel quality measurements and the active data transmissions are performed using an off-the-shelf Android-based UE (Samsung Galaxy S5 Neo, Model SM-G903F) which executes the measurement application. TCP transmissions are performed periodically each 10 s in uplink and downlink direction through the public LTE network. The exchanged payload is chosen randomly in the range of 0.1 MB to 10 MB.

During the drive tests, the entire cell activity is captured by three synchronized FALCON¹ sniffers, each placed in one of the base station's sectors in line of sight to the antenna. Each sniffer comprises a common Laptop running the FALCON software and an attached USRP B210 SDR by Ettus Research with a dipole antenna receiving the signal.

¹FALCON is available at <https://github.com/falkenber9/falcon>

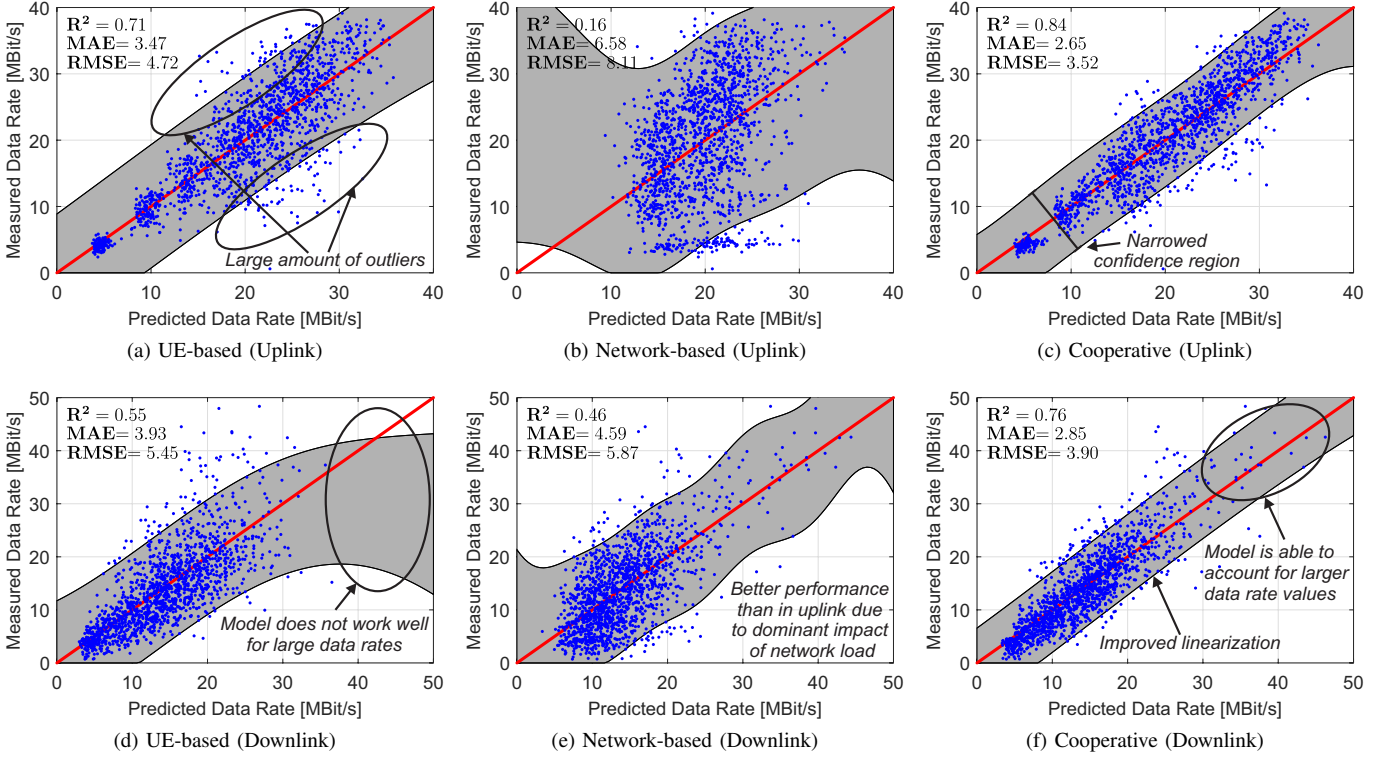


Fig. 5. Performance comparison of different RF data rate prediction approaches in uplink and downlink direction. Network-based predictions (b) and (e) only consider cell load information features \mathbf{X}_{Net} from the FALCON measurements. The gray area shows the 0.95 confidence area derived by applying GPR on the results of the prediction model. Diagonal lines illustrate perfect predictions. MAE and RMSE are expressed in MBit/s.

The considered data set is the result of 92 real world drive tests and consists of measurements for 3027 data transmissions. It includes measurements during peak noon, while the mobile network is very congested, as well as measurements during the night, with almost no activity by other participants.

B. Machine Learning-based Data Analysis

All data analysis tasks are carried out with Waikato Environment for Knowledge Analysis (WEKA) [25]. In order to avoid overfitting, we apply 10-fold cross validation and analyze the statistical derivations between the different folds. For assessing the quality of the data rate prediction, we consider multiple typical quality measures for regression tasks. The *coefficient of determination* R^2 is a statistical metric widely used by the related work. It describes the amount of response variable derivation that is explained by the trained regression model and is calculated as

$$R^2 = 1 - \frac{\sum_{i=1}^N (\tilde{y}_i - y_i)^2}{\sum_{i=1}^N (\bar{y} - y_i)^2} \quad (1)$$

with the current prediction \tilde{y}_i , the current label y_i , the mean data rate \bar{y} , and the number of measurement samples N . In addition, we consider Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) which are defined as

$$\text{MAE} = \frac{\sum_{i=1}^N |\tilde{y}_i - y_i|}{N}, \quad \text{RMSE} = \sqrt{\frac{\sum_{i=1}^N (\tilde{y}_i - y_i)^2}{N}}.$$

V. RESULTS OF THE REAL WORLD PROOF-OF-CONCEPT EVALUATION

In this section, we present and discuss the results of the real world proof-of-concept evaluation. At first, the achievable prediction performance is compared for different machine learning models for the UE-based and cooperative approaches. Fig. 4 shows the resulting RMSE values. It can be seen that the cooperative approach is able to reduce the average RMSE by up to 25% in uplink and 30% in downlink transmission direction by considering features that indicate the current network load. In all variants, the lowest RMSE is achieved by the RF model which is in consensus with related work [17], [11], [12]. However, it is remarkable that M5 achieves an almost comparable performance level, as the model is far less complex than the RF. In the downlink direction, the machine learning models show a more consistent behavior. As discussed in the following paragraph, the traffic load has a dominant impact on the resulting data rate which results in a more linear relationship between the considered features.

Based on these observations, the behavior of the RF model is further investigated. Fig. 5 shows the resulting prediction performance for UE-based, network-based, and the proposed cooperative approach. The statistical behavior of the model is further illustrated with a confidence region derived by applying Gaussian Process Regression (GPR) on the prediction results. It can be seen that the UE-based approach achieves a generally good correlation between predictions and measurements. It

should be denoted that this methodological approach only requires an off-the-shelf UE to perform the measurements, which means a lower hardware-related effort than the SDR-enabled cooperative approach. However, large outliers occur due to missing network load information. Pure network-based prediction is unaware of the radio channel conditions of the targeted mobile UE and only able to consider the current network load. As the downlink is typically more congested than the uplink [5], the achievable data rate is more determined by the network-related than the channel-related features. Therefore, the prediction works more reliable in the downlink direction. In both transmission directions, the proposed cooperative approach is able to compensate the major limitations of the individual approaches. As a result, the error spread is significantly reduced which results in a more linear and more narrow confidence interval.

VI. CONCLUSION

In this paper, we presented a cooperative approach for cellular data rate prediction which brings together UE-based channel quality sensing with network-based load estimation in vehicular scenarios. In order to mimic the possible behavior of network-assisted throughput prediction in future 6G networks, a real world performance evaluation based on the FALCON sniffer was conducted in a vehicular context. It was shown that SDR-based approaches are capable of extracting network load information based on control channels analysis and that this knowledge can be utilized to significantly improve the data rate prediction accuracy for mobile UEs in both transmission directions. Within 5G networks, data analytics-based (e.g., NWDAF-enabled) network optimization is currently solely considered for the network infrastructure side. Although it is not clear which kind of intelligence future 6G networks will implement, we strongly advertise that the obtained traffic load information should be actively shared with the UEs in order to catalyze network-assisted UE-based optimization methods. This way, further enhancements of the prediction accuracy can be expected as the need for synchronizing multiple time series measurements is removed.

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