Client-Based Intelligence for Resource Efficient Vehicular Big Data Transfer in Future 6G Networks

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***Abstract*—Vehicular big data is anticipated to become the "new oil" of the automotive industry which fuels the development of novel crowdsensing-enabled services. However, the tremendous amount of transmitted vehicular sensor data represents a massive challenge for the cellular network. A promising method for achieving relief which allows to utilize the existing network resources in a more efficient way is the utilization of intelligence on the end-edge-cloud devices. Through machine learning-based identification and exploitation of highly resource efficient data transmission opportunities, the client devices are able to participate in overall network resource optimization process. In this work, we present a novel client-based opportunistic data transmission method for delay-tolerant applications which is based on a hybrid machine learning approach: Supervised learning is applied to forecast the currently achievable data rate which serves as the metric for the reinforcement learning-based data transfer scheduling process. In addition, unsupervised learning is applied to uncover geospatially-dependent uncertainties within the prediction model. In a comprehensive real world evaluation in the public cellular networks of three German Mobile Network Operators (MNOs), we show that the average data rate can be improved by up to 223 % while simultaneously reducing the amount of occupied network resources by up to 89 %. As a side-effect of preferring more robust network conditions for the data transfer, the transmission-related power consumption is reduced by up to 73 %. The price to pay is an increased Age of Information (AoI) of the sensor data.**

I. Introduction

The various sensing and communication capabilities of modern vehicles have brought up *vehicular crowdsensing* [1], [2] as a novel method for acquiring various kinds of measurement data. Hereby, the mobility behavior of the vehicles is exploited to dynamically cover large areas with sensing capabilities. It is expected that the *vehicle-as-a-sensor* approach will catalyze the development of data-driven applications such as distributed creation of High Definition (HD) environmental maps, traffic monitoring, predictive maintenance, road roughness detection, and distributed weather sensing [3].

As pointed out by [4], a high amount of these target applications — in particular, *mapping* services — can be characterized as *delay-tolerant*. Hereby, the applications do not require immediate data delivery but specify soft deadlines within which the received information is considered meaningful. In their empirical analysis, the authors of [5] analyzed the properties of 32 existing crowdsensing systems from which 23 were found to be compatible with *store-and-forward* data delivery mechanisms. As an example, the

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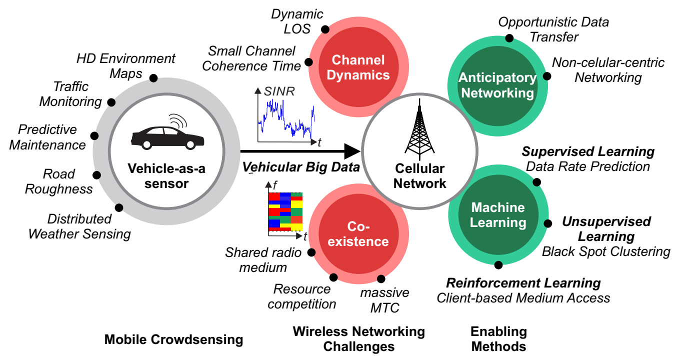


Fig. 1: Overview about applications, challenges, and enabling methods for vehicular big data in cellular communication networks.

Automotive Edge Computing Consortium (AECC) has analyzed the requirements for distributed construction of HD environmental maps for automated driving in a recent white paper [6]. For permanent and transient static objects (e.g., road network, surrounding buildings, road work), an update interval in the range of multiple hours is proposed. Even for reporting dynamic obstacles such as other traffic participants, periodic data transfer with an interval of 15 s is considered sufficient.

The rise of *vehicular big data* will confront the cellular network with tremendous amounts of resource requirements for vehicular massive Machine-type Communication (mMTC). Since the provision of additional spectrum resources through densification of the network infrastructure is highly cost-intense, it would be preferable to utilize the *existing* resources in a more efficient way through application of machine learning-enabled network intelligence. An overview about the corresponding applications, challenges, and solution approaches for vehicular big data transfer in cellular networks, which is further described in the following paragraphs, is shown in Fig. 1. Within the scope of this work, we apply a pragmatic approach which utilizes existing methods from the machine learning domain. However, it is remarked that these enabling methods are themselves subject to active developments in their corresponding research communities. Therefore, it can be expected that future advancements within the neighboring fields can be utilized for further improving the resource efficiency of vehicular big data transfer.

While the current deployments and research efforts for the emerging 5G networks focus on network-side intelligence (e.g., the Network Data Analytics Function (NWDAF) allows machine learning-based load analysis of network slices [7]), researchers agree that *pervasive* intelligence will be one of the

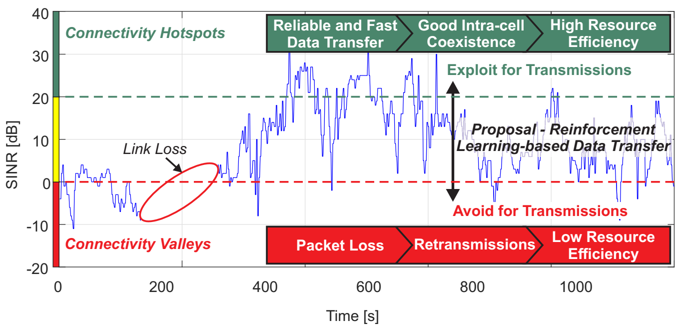


Fig. 2: Example for the dynamics of the vehicular radio channel. For optimizing the achievable resource efficiency, client-based intelligence is used to exploit connectivity hotspots and avoid transmissions during connectivity valleys.

key drivers for future 6G networks which are expected to be deployed around 2030 [8], [9]. As a consequence, this will catalyze the development of *non-cellular-centric* networking mechanisms such as *end-edge-cloud* orchestrated intelligence [10] where locally applied machine learning mechanisms allow the client devices to participate in network functions and contribute to the overall network optimization.

An important observation which motivates our contribution is that regular fixed-interval data transmission schemes experience a large variance of the network quality (see Fig. 2). In order to avoid packet errors and retransmission, the mobile User Equipments (UEs) dynamically adjust the Modulation and Coding Scheme (MCS) to achieve a better robustness in challenging channel situations. However, since lower MCSs reduce the transmission efficiency and increase the occupation time of the Physical Resource Blocks (PRBs), this method results in a wastage of network resources and has a negative impact on the intra-cell coexistence.

In this work, we exploit the delay-tolerant nature of many vehicular crowdsensing applications as well as the mobility of the vehicles for improving the cellular resource efficiency. Client-based intelligence is applied in order to autonomously schedule the data transfer with respect to the anticipated transmission efficiency. Our proposed method brings together and extends the results of previous work for reinforcement learning-enabled data transfer in vehicular scenarios [11], [12].

The contributions provided by this paper are summarized as follows:

- Presentation of Black Spot-aware Contextual Bandit (BS-CB) as a novel **hybrid machine learning** approach for opportunistic data transfer for mobile and vehicular networks.
- Comprehensive **real world** performance analysis and comparison to existing data transfer methods.
- Proof-of-concept evaluation for compensating concept drift situations of the data rate prediction through **online learning**.
- The raw results and the developed measurement software are provided in an **open source** way. [1]

[1] https://github.com/BenSliwa/rawData_opportunistic_data_transfer

The remainder of the paper is structured as follows. After discussing the related work in Sec. II and giving an overview about the different evolution stages of the novel method in Sec. III, we present the reinforcement learning-based solution approach in Sec. IV. Afterwards, the methodological setup is introduced in Sec. V and the achieved results are presented and discussed in Sec. VI. Based on the resulting insights, we derive recommendations for future 6G networks which are summarized in Sec. VII.

II. Related Work

Machine learning has received tremendous attention within the wireless research community due to its inherent capability of implicitly considering hidden interdepencies between measurable indicators which are too complex to model analytically. Different summary papers [13]–[16] provide comprehensive information about using machine learning methods for optimizing wireless networks. Three major machine learning disciplines are distinguished:

- **Supervised** learning allows to learn a model f_{ML} on *features* $\mathbf{X}$ with *labeled* data $\mathbf{Y}$ such that $f : \mathbf{X} \rightarrow \mathbf{Y}$. After the training phase, the model can be utilized to make predictions $\tilde{y}$ on novel unlabeled data $\mathbf{x}$ such that $\tilde{y} = f(\mathbf{x})$. For this purpose, popular model classes are (deep) Artificial Neural Networks (ANNs) [17], Classification and Regression Trees (CARTs)-based methods such as Random Forests (RFs) [18], and Bayesian models such as Gaussian Process Regression (GPR) [19].
- **Unsupervised** learning is applied to cluster measurements based on patterns in non-labeled data sets. A popular method for this category is the k-means [20] algorithm.
- **Reinforcement** learning [21], [22] teaches an *agent* to autonomously perform favorable *actions* in a defined *environment* by learning from the observed *rewards* of previously taken actions. Q-Learning [23] represents the foundation for most more complex methods such as deep reinforcement learning.

Within commercial deployments of emerging 5G networks, the implementation of machine learning-based intelligence mainly focuses on the network infrastructure side. NWDAF [7], [24] is a novel machine learning-enabled network function which is used by the MNOs to determine and predict the network load. Different use-cases that could exploit this information — e.g., traffic routing, mobility management, load balancing, and handover optimization — are motivated in [25]. Among others, the white paper of [9] envisions *pervasive machine learning* as one of the fundamental enabling methods for future 6G networks which are expected to be deployed around 2030. As a consequence of the trend of bringing intelligence closer towards the client devices, resource-aware machine learning has become an emerging research topic. A comprehensive summary about resource aspects for edge-based intelligence is provided by Park et al. in [26].

The recent advancements in machine learning-based data analysis have also led to the rise of the end-to-end modeling paradigm for wireless communication systems [27] and have

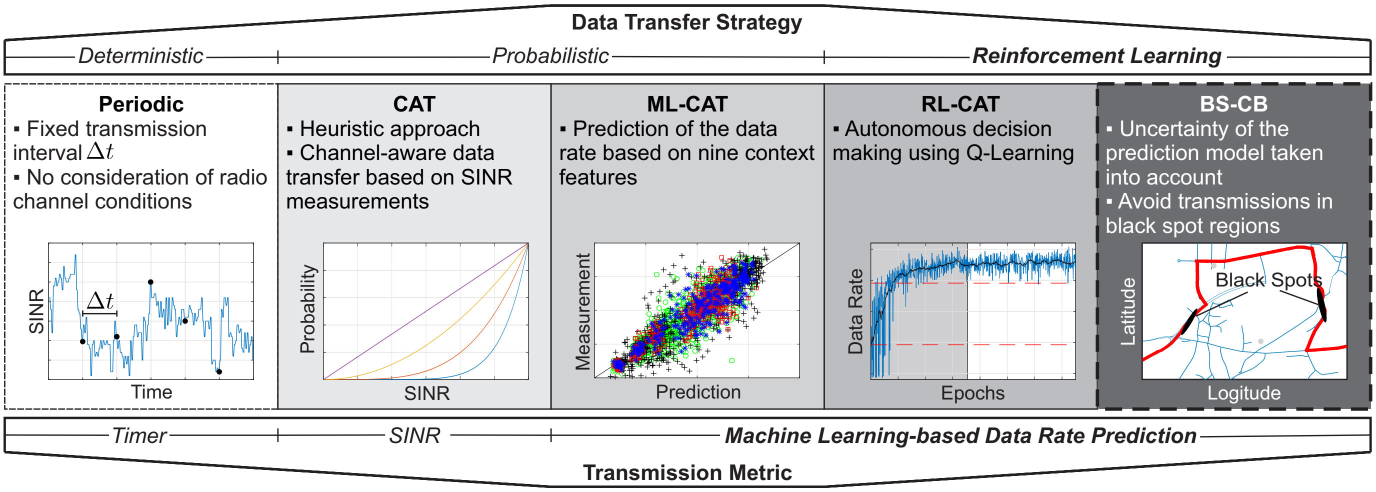


Fig. 3: Continuity of context-aware approaches for opportunistic data transmissions in vehicular networks.

catalyzed the development of novel data-driven performance evaluation methods. Data-driven Network Simulation (DDNS) [28], [29] allows to analyze the performance of wireless communication systems by replaying empirically acquired context traces. The end-to-end behavior of the observed target Key Performance Indicator (KPI) is then derived by a combination of deterministic and probabilistic machine learning models which mimics the statistical derivations of the real world measurements. In comparison to conventional system-level network simulation [30], this method is able to achieve a better modeling accuracy of radio propagation effects in concrete real world evaluation scenarios and achieves a massively higher computational efficiency. Another advantage is a reduction of the simulation setup complexity since the end-to-end analysis approach solely relies on the acquired data and does not require to parameterize communicating entities.

Anticipatory mobile networking [31] is a novel wireless communications paradigm which aims to optimize decision processes in communication systems through explicit consideration of *context* information. Since mobile and vehicular networks are inherently impacted by the interdependency of mobility and radio channel dynamics [32], machine learning-enabled anticipatory networking is a promising approach for system optimization in this domain. As an example, Dalgkitsis et al. [33] utilize mobility prediction jointly with deep learning for improving the service orchestration process in 5G vehicular networks.

Non-cellular-centric networking [34] integrates the network clients as part of the network fabric and allows them to contribute explicitly or implicitly to network management functions. This approach allows to exploit the capability of the clients to sense their environments for opportunistically scheduling data transmissions for delay-tolerant applications [35] in a context-aware manner. In [36], Shi et al. point out that network congestion has a large short-term variance and that traffic peaks can be compensated by delaying transmissions. Therefore, the authors propose the Collaborative Application-Aware Scheduling of Last Mile Cellular Traffic (CoAST) system which applies a collaborative infrastructure-assisted optimization approach based on dynamic pricing. Hereby, the announced traffic demands of the UEs are used by a central entity which computes and broadcasts the projected data transfer prices for a given future time window. This information is then used by the UEs to schedule their transmissions with respect to the trade-off between price and additional delay. Peek-n-sneak [37] and Client-side Adaptive Scheduler That minimizes Load and Energy (CASTLE) [38] are distributed transmission scheduling approaches which rely on a threshold decision for performing or delaying the data transfer. Both approaches use different network quality indicators (Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal-to-interference-plus-noise Ratio (SINR)) for predicting the current network load based on a Radial Basis Function (RBF) Support Vector Machine (SVM).

Data rate prediction can serve as a metric for anticipatory decision making such as opportunistic data transfer [39] and dynamic Radio Access Technology (RAT) selection. The predictions can either be performed *actively* or *passively*. Active prediction methods apply time series analysis – e.g., based on Long Short-term Memory (LSTM) methods as considered in [40], [41] – and monitor the behavior of ongoing data transmissions. Since the need to continuously transmit data is opposed to the considered opportunistic medium access strategy, this work focuses on passive prediction approaches which have been investigated by different authors. The key insights are summarized as follows:

- Radio channel indicators (e.g., defined according to 3GPP TS 36.213 [42]) are highly correlated to the observed data rate and can serve as meaningful information for predicting the latter [43]–[45].
- Due to the *curse of dimensionality* [46], complex models such as ANN-based *deep learning* approaches require a significantly higher amount of training data than simpler methods such as CARTs. As typical data sets in the wireless communication domain are comparably small [9], less complex methods often achieve a higher prediction accuracy [29], [47].
- For the derivation of generalizable prediction models, it is

important to integrate application-layer knowledge about the *payload size* of the data packet to be transmitted [48]. This way, the prediction is able to implicitly account for the interdependency between transmission duration and channel coherence time as well as payload-overhead-ratio and protocol-specific aspects such as the slow start mechanism of the Transmission Control Protocol (TCP).

- A low data aggregation granularity should be preferred: Few models with large data sets (e.g., a single prediction model per MNO) achieve a better average prediction performance than a large amount of highly-specific models (e.g., dedicated prediction models for each evolved Node B (eNB)) [48], [49].
- Although temporal effects have a significant impact on the network load, the time of day is negligible if load-dependent network quality indicators such as RSRQ are considered in the data set [48], [50].

In addition to these purely client-based approaches, the authors of [51] have analyzed a possible implementation for *cooperative* data rate prediction in future 6G networks where the network infrastructure actively announces network load information to the mobile clients. In an initial feasibility study, it is shown that the cooperative approach is able to reduce the Root Mean Squared Error (RMSE) by 25 % in uplink and 30 % in downlink direction

III. Towards Reinforcement Learning-enabled Opportunistic Data Transfer

Different opportunistic data transfer methods have build the foundation for the proposed BS-CB method. The different evolution stages are shown in Fig. 3.

Periodic data transfer represents the regular approach for transmitting Machine-type Communication (MTC) data. The medium access is based on a fixed timer interval Δt which transmits the data regardless of the radio channel conditions.

Channel-aware Transmission (CAT) [52] is a probabilistic opportunistic data transfers method which schedules the medium access based on measurements of the SINR. Data is buffered locally until a transmission decision is made for the whole buffer. The transmission probability $p_{\mathrm{TX}}(t)$ is computed as

$$p_{\mathrm{TX}}(t) = \begin{cases} 0 & \Delta t < \Delta t_{\min} \\ 1 & \Delta t > \Delta t_{\max} \\ \left(\frac{\Phi(t)-\Phi_{\min}}{\Phi_{\max}-\Phi_{\min}}\right)^{\alpha} & \text{else} \end{cases} \tag{1}$$

with Φ being the transmission metric – the SINR(t) measurement – with a defined value range $\{\Phi_{\min}, \Phi_{\max}\}$. Δt represents the time since the last transmission has been performed. $\Delta t_{\min}$ is used to guarantee a minimum packet size and $\Delta t_{\max}$ ensures that the AoI does not exceed the requirements of the target application. The exponent α allows to control the preference of high metric values within the data transfer process.

Machine Learning CAT (ML-CAT) [39], [53] is a machine learning-based extension to CAT. Due to the short-term fluctuations of the SINR, the transmission decision is performed based on data rate predictions which are obtained from an RF model (see Sec. IV-A). While the actual transmission is still performed based on Eq. 1, the considered metric Φ corresponds to the predicted data rate $\tilde{S}(t)$.

Reinforcement Learning CAT (RL-CAT) [11] is a first reinforcement learning-based variant of the ML-CAT method which replaces the probabilistic medium access with a Q-learning approach aiming to maximize the data rate of the *individual* sensor data transmissions. The predicted data rate and the elapsed buffering time form the context tuple $\mathbf{c_t} = (\tilde{S}(t), \Delta t)$ are used to lookup up the action — `IDLE` or `TX` — with the highest Q-value from a Q-table. The latter is trained as

$$Q(\mathbf{c_t}, a) = (1-\alpha) \cdot Q(\mathbf{c_t}, a) + \alpha \left[r_a + \lambda \cdot \max_a Q(\mathbf{c_{t+1}}, a) \right] \tag{2}$$

whereas α corresponds to the learning rate, r_a is the reward of the action a, λ represents the discount factor, and $\mathbf{c_{t+1}}$ is an estimation for the Q-value after a has been executed. In classical Q-Learning, it is assumed that the decision making of the agent causes a sequential improvement of its *state* within the environment and ultimately leads to reaching an "optimal" target state. However, as further discussed Sec. IV, in the considered opportunistic data transfer use case, the agent-related impact on the state of the environment is negligible due to the dominance of external influences such as the channel and network load dynamics: Even if the agent was capable of performing hypothetical "optimal" actions, its state — represented by the context tuple $\mathbf{c_t}$ — would be still determined by the impact of the non-controllable influence factors. Therefore λ is set to 0 which results in a simplified Q-Learning variant

$$Q(\mathbf{c_t}, a) = (1-\alpha) \cdot Q(\mathbf{c_t}, a) + \alpha \cdot r_a. \tag{3}$$

that implements a myoptic approach focusing on optimizing the immediate reward of the taken actions.

IV. Reinforcement Learning-based Opportunistic Data Transfer with BS-CB

In this section, we present the novel BS-CB method. According to the classification scheme for edge intelligence provided by [54], the proposed data transfer method represents a *level 3: on-device inference* edge intelligence implementation where the model is trained in the cloud/offline and inference is run completely locally.

A schematic overview about the interaction between the different logical entities is shown in Fig. 4.

- The actual opportunistic data transfer is modeled as a reinforcement learning **agent** which senses its *environment*, performs *actions* and observes the resulting *rewards*.
- Hereby, the **environment** is represented by the real world cellular network. Classical reinforcement learning assumes that the actions taken by the agent change the *state* of the environment. However, in the considered vehicular scenarios, the properties of the environment are highly *time-variant* due to the dynamically changing radio channel conditions mainly related to the mobility behavior of the mobile UE. In addition, other users of

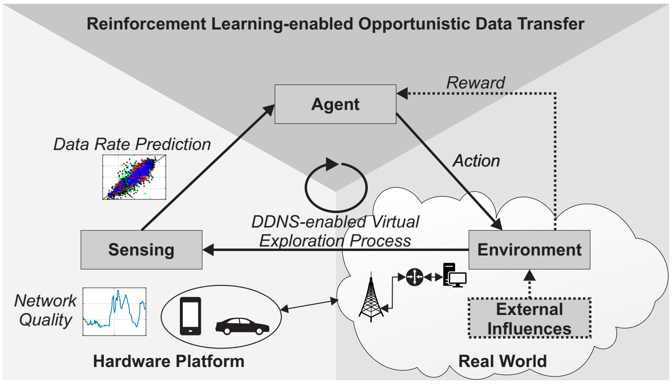


Fig. 4: Interaction between the different logical entities within a reinforcement learning setup for opportunistic data transfer.

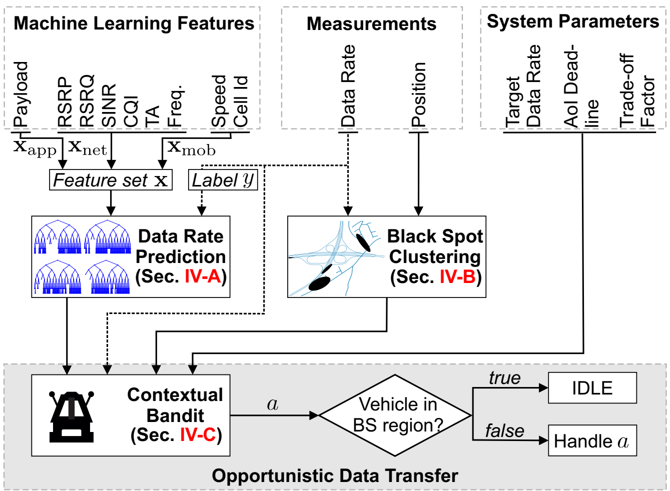


Fig. 5: Overall system architecture model of the proposed BS-CB method.

the cellular network consume network resources which leads to the conclusion that the state of the environment mainly depends on the *external influences*.

- The **sensing** of the environment is performed through the hardware platform which observes context indicators. In order to reduce the dimensionality of the reinforcement learning problem, data rate prediction is applied.

The overall system model of the novel BS-CB is shown in Fig. 5. BS-CB implements a hybrid approach which brings together all major machine learning disciplines. Supervised learning is applied to predict the achievable data rate based on measured context indicators. Unsupervised learning is then utilized to detect geospatially-dependent uncertainties of the prediction model. Finally, the reinforcement learning-based autonomous data transfer uses the acquired information for optimizing the resource efficiency of vehicular data transmissions. In the following paragraphs, the three main components of the proposed methods are introduced in further details.

A. Supervised Learning: Data Rate Prediction

The overall feature set $\mathbf{x}$ is composed of nine different features from multiple context domains:

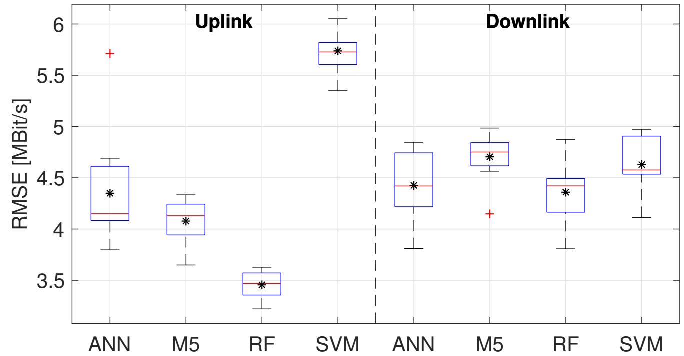


Fig. 6: Resulting data rate prediction performance for different regression models on the *MNO A* data set. *ANN:* Artificial Neural Network, *M5*: M5 Regression Tree, *RF*: Random Forest, *SVM*: Support Vector Machine

- **Network context** $\mathbf{x}_{\mathrm{net}}$: RSRP, RSRQ, SINR, Channel Quality Indicator (CQI), Timing Advance (TA)
- **Mobility context** $\mathbf{x}_{\mathrm{mob}}$: Velocity of the vehicle, cell id of the connected eNB
- **Application context** $\mathbf{x}_{\mathrm{app}}$: Payload size of the data packet to be transmitted

The data rate is then predicted based on a regression model f_{ML} as $\tilde{S}(t) = f_{\mathrm{ML}}(\mathbf{x})$. As a preprocessing step, we compare the prediction performance of different machine learning models whereas the parameterization of each model has been optimized based on grid search:

- **Artificial Neural Network (ANN)** [17] with two hidden layers with 10 neurons per hidden layers and sigmoid activation function, momentum $\alpha = 0.001$, learning rate $\eta = 0.1$, and 500 training epochs.
- CART methods **M5 Regression Tree (M5)** and **Random Forest (RF)** [18] with 100 random trees and maximum depth 15.
- **Support Vector Machine (SVM)** with RBF kernel and Sequential Minimal Optimization (SMO) training.

The resulting RMSE of the data rate prediction models on the *MNO A* data set of [48] is shown Fig. 6. In both evaluations, the lowest prediction error is achieved by the RF model. In uplink direction, different context indicators have specific regions of application: As discussed in [48], RSRQ is an important indicator for the data rate in cell edge regions and SINR has a higher impact on the latter in the center of the cell — both can be distinguished through considering the RSRP. These interval-wise scope regions match well with the condition-based model architecture of the RF model. However, in downlink transmission direction, the differences between the considered prediction models are less significant. This observation can be explained through consideration of the findings of [31]: In downlink direction, the resulting data rate is mostly related to the cell load which is partially represented by the RSRQ. The presence of this dominant feature results in a less complex learning task. Since the RSRQ is only an implicit indicator for the current network load, the resulting RMSE is relatively high.

Due to these observations, we apply the RF model for

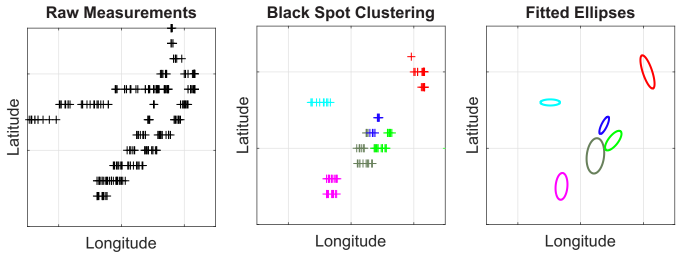


Fig. 7: Steps of the black spot clustering process.

performing the context-based data rate predictions in the remainder of this paper.

B. Unsupervised Learning: Black Spot Clustering

An important observation of previous work [11] is that the resulting data rate prediction accuracy in vehicular scenarios has a *geospatial dependency*: Large outliers often occur *cluster-wise* due to local effects such as eNB handovers, cell switches, and environment-dependent sporadic link loss. Although the knowledge about these mechanisms does not explicitly allow us to compensate the undesired effects, it can be exploited within the opportunistic data transmission processes as a measurement for the *uncertainty* of the prediction model: Transmissions should be avoided if the prediction model is currently in an unreliable state and does not allow to make a precise statement about the achievable end-to-end performance. We call these areas *black spots* based on the usage of the term in traffic satefy where it refers to regions with a significantly increased probability for collisions of vehicles.

The proposed black spot-aware networking approach is divided into the unsupervised learning-based offline data analysis and the online application. The **offline data analysis** consists of multiple steps which are visualized in Fig. 7.

1) **Geo-clustering**: Unsupervised learning based on *k-means* [20] is applied in order to cluster the transmission locations into a total amount of N_c clusters.
2) **Black spot detection**: For each cluster c, the RMSE (see Sec. V) of the data rate prediction results is computed and compared to a threshold value RMSE_{max}. All clusters that exceed the given upper limit are labeled as *black spot clusters*.
3) **Ellipse fitting**: All detected black spot clusters are fitted to rotated ellipses in order to allow their later online consideration within the opportunistic data transmission process. Hereby, the length a of the ellipse is calculated based on the dominant intra-cluster distance vector.

The impact of considering information about black spot regions within the prediction model is shown in Fig. 8. While Fig. 8 (a) shows the resulting prediction performance of the overall data set which consists of black spot and non-black regions, the separation of the prediction model allows to improve the prediction accuracy for the non-black spot regions as shown in Fig. 8 (b). In the following, we will use this variant for predicting the data rate as the metric of the opportunistic data transmission process.

For the **online application**, the vehicle's position $\mathbf{P}$ is compared against all black spot ellipses with corresponding ellipse centroid $\mathbf{P}_i$ based on an intersection test for α-rotated ellipses. The vehicle is within the considered elliptic region if the following condition is fulfilled:

$$\frac{(c \cdot \mathbf{v}.x + s \cdot \mathbf{v}.y)^2}{a^2} + \frac{(s \cdot \mathbf{v}.x - c \cdot \mathbf{v}.y)^2}{b^2} \leq 1 \tag{4}$$

with $\mathbf{v} = \mathbf{P} - \mathbf{P}_i$, $c = \cos\alpha$, $s = \sin\alpha$, and α being the ellipse rotation. An overview about the detected black spot regions for *MNO A* in uplink direction is shown in Fig. 9.

C. Reinforcement Learning: Contextual Bandit-based Data Transfer

The actual opportunistic data transfer is modeled as a Linear Upper Confidence Bound (LinUCB) [55] contextual bandit whereas the *arms* of the bandit correspond to the possible actions:

- $\mathbf{a}_{\mathbf{IDLE}}$ leads to a local buffering of the newly acquired data as the current network quality is not considered appropriate for allowing resource efficient data transfer. It is assumed that due the mobility behavior of the vehicle, the mobile UE will encounter a more suitable transmission opportunity in the future.
- $\mathbf{a}_{\mathbf{TX}}$ causes the transmission of the whole buffered data.

The context-aware arm selection process is performed based on a sequence of matrix-vector multiplications as

$$a = \arg\max_{a \in \mathbf{A}} \left(\underbrace{\hat{\theta}_a^T \mathbf{c}}_{\text{Estimated reward}} + \underbrace{\alpha \sqrt{\mathbf{c}^T \mathbf{A}_a^{-1} \mathbf{c}}}_{\text{UCB}} \right). \tag{5}$$

Hereby, the estimated reward is derived by ridge regression whereas $\hat{\theta}_a$ represents the regression coefficients of arm a which are updated during the reinforcement learning process and $\mathbf{c} = (\tilde{S}(t), \Delta t)$ is the d-dimensional context tuple consisting of the predicted data rate $\tilde{S}(t)$ and the current buffering time Δt.

$\mathbf{A}_a$ is computed as $\mathbf{A}_a = \mathbf{D}_a^T \mathbf{D}_a + \mathbf{I}_a$ with $\mathbf{I}_a$ being a d-dimensional identity matrix and $\mathbf{D}_a$ being the $m \times d$ matrix which contains the m previously observed context tuples. The constant exploration parameter α controls the greediness of the algorithm and is computed as

$$\alpha = 1 + \sqrt{\frac{\ln(2/\delta))}{2}} \tag{6}$$

based on the only system parameter δ. The smaller the value of α, the more greedy the algorithm behaves, meaning that it will more likely *exploit* actions that currently seem to be optimal.

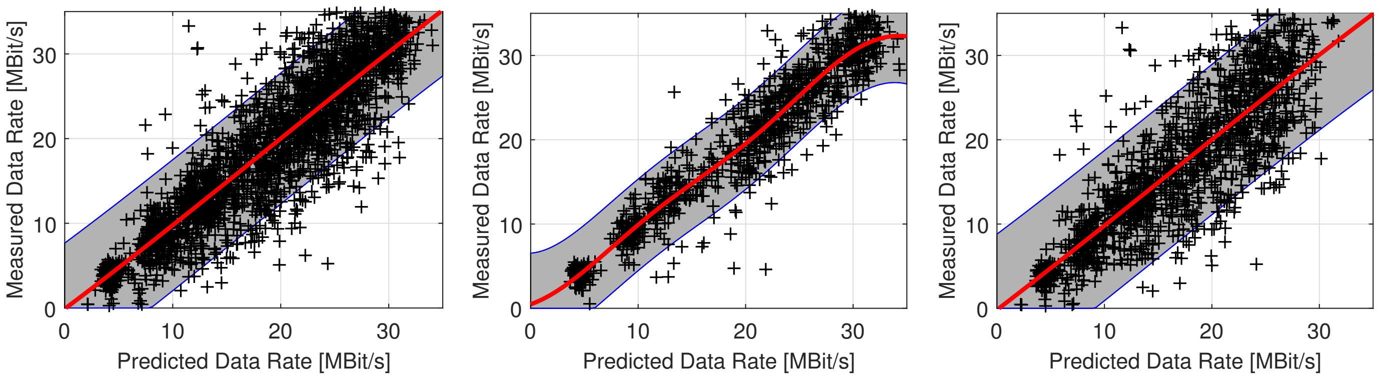
After each performed action, the regression coefficients are updated based on the observed reward r_a as

$$\hat{\theta}_a \leftarrow \mathbf{A}_a^{-1} \mathbf{b}_a \tag{7}$$

with

$$\mathbf{b}_a \leftarrow \mathbf{b}_a + r_a \cdot \mathbf{c} \tag{8}$$

Hereby, $\mathbf{b}_a$ is initialized as a d-dimensional zero vector. The reward functions are computed action-specific, for the `TX`



(a) Overall prediction model (b) Non-black spot prediction model (c) Only black spot prediction model

Fig. 8: The overall prediction model is separated into a more precise model for non-black spot regions and a less precise model for black spot regions. The gray area shows the behavior of a 0.95-confidence area derived by applying a GPR model on the results of the prediction model.

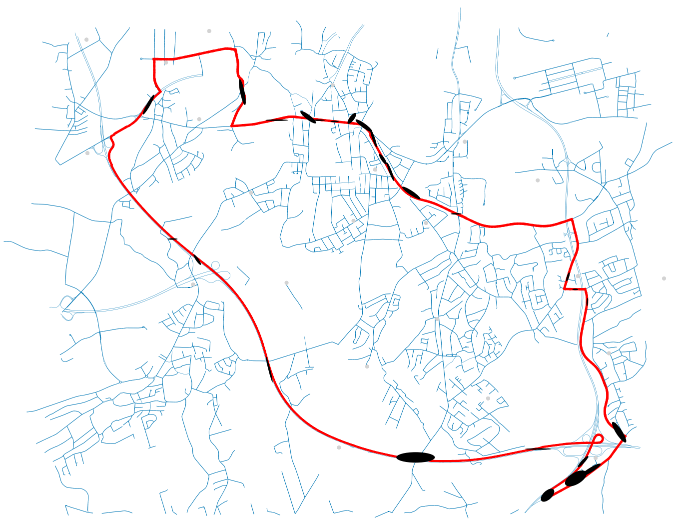


Fig. 9: Resulting black spot regions along the evaluation track for *MNO A* in uplink direction (Map: ©OpenStreetMap contributors, CC BY-SA).

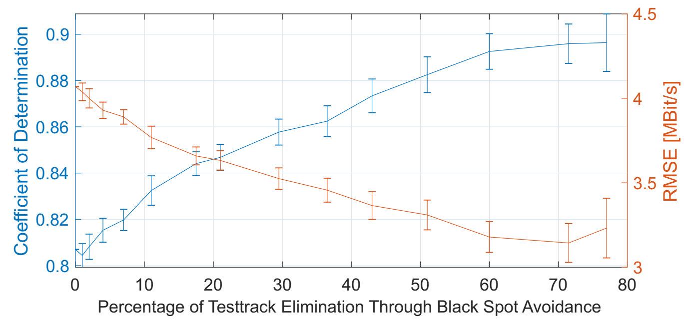


Fig. 10: Trade-off between performance improvement of the data rate prediction and tolerable reduction of the transmission opportunities (*MNO A* uplink).

action, the reward is derived as:

$$r_{\mathrm{TX}}(S, \Delta t) = \frac{\omega \cdot (\tilde{S} - S^*)}{S_{\max}} + \frac{\Delta t \cdot (1 - \omega)}{\Delta t_{\max}} \tag{9}$$

whereas the trade-off factor w controls the fundamental trade-off between data rate optimization and AoI optimization. S^* represents a target data rate which should be approached and $S_{\max}$ is the empirically observed maximum data rate of the network. Δt is an application-specific deadline for the tolerable AoI.

The reward of the `IDLE` action is computed as:

$$r_{\mathrm{IDLE}}(\Delta t) = \begin{cases} \Omega & \Delta t \geq \Delta t_{\max} \\ 0 & \text{else} \end{cases} \tag{10}$$

whereas Ω is chosen as a negative number which ensures that the estimated reward of the `TX` action is superior to the reward of the `IDLE` action if Δt exceeds the AoI deadline $\Delta t_{\max}$. As a result, the data is transferred immediately regardless of the radio channel conditions.

After the contextual bandit has made a transmission decision, the information about the black spot regions is leveraged: If the vehicle is currently within a black spot region, the data transfer is postponed since the prediction model cannot be trusted. As a result of this approach, there exists a trade-off between the achievable improvement of the data rate prediction accuracy and a reduction of the usable percentage of the track for performing data transmissions. Fig. 10 shows the resulting R^2 and RMSE values with respect to the tolerable percentage of track elimination — the total spread of the black spot regions over the overall track length — for the *MNO A* uplink data set of [48]. It can be seen that the reduction of transmission opportunities allows to significantly improve the performance of the prediction model. Where the curves convergence, the model only considers highly reliable connectivity hotspots appropriate for the data transfer. In the following, we allow a maximum track reduction of 20 %.

V. Methodology

In this section, an overview about the research methods, tools, and performance metrics is provided. A summary about

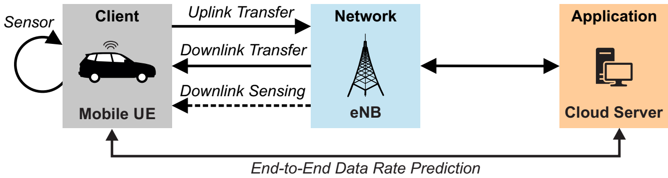


Fig. 11: Network model of the real world performance evaluation.

relevant parameters of the novel transmission scheme is given in Tab. I

TABLE I: Default parameters of the evaluation setup

Parameter	Value
Maximum buffering time $\Delta t_{\max}$	120 s
Trade-off factor w	0.9
Deadline violation punishment Ω	-1
Exploration parameter δ	0.1
Number of clusters N_c	100
MNO-specific black spot threshold $\mathrm{RMSE}_{\max}$	3, 2.25, 2.5
Periodic data transfer interval Δt	10 s

A. Real World Data Acquisition

For the empirical performance comparison, five test drives are performed in the real world for each of the transmission schemes. Fig. 11 shows the network model of the evaluation. A virtual sensor application generates 50 kB of sensor data per second. Data transmissions are performed from a moving vehicle through the public Long Term Evolution (LTE) networks of three German MNOs in uplink and downlink direction via TCP. The evaluations are carried out along a 25 km long evaluation track (Fig. 9) which contains highway and suburban regions with varying building densities and speed limitations. In total, 8563 transmissions – 13.61 GB of transmitted data – are performed. The passive measurement of the context indicators as well as the active data transmission are performed on an `Android`-based UE (Galaxy S5 Neo, Model SM-G903F) based on a novel application. The latter is provided in an open source way[2].

B. Performance Indicators

Within the real world performance comparison in Sec. VI, multiple KPIs are considered which are obtained as follows.

End-to-end data rate: The evaluation of the achieved data rate is performed at the application level and represents the transmission efficiency of the considered transmission schemes. The actual measurements are performed at a cloud server.

AoI: Due to the local buffering process implied by the opportunistic data transfer approach, each transmitted data packet consists of multiple sensor packets. In order to analyze the freshness of the received sensor information, the generation time of the *oldest* sensor packet within the received overall data is considered.

Network resources: For estimating the number of PRBs of performed transmissions in a postprocessing step, we revert the procedure described in [56]. Hereby, the CQI measurements are utilized to determine the MCS and Transport Block Size (TBS) indices from the 3GPP TS 36.213 lookup tables. Based on this information and the measured data rate, the number of PRBs is inferred.

Power consumption: The resulting power consumption of a mobile UE is mainly determined by the applied transmission power P_{TX} which controls the stage of the power amplifiers. Unfortunately, `Android`-based UEs do not expose this information to the user space. However, the analysis in [57] has shown that P_{TX} can be inferred from radio signal measurements since it is highly correlated to distance-dependent indicators such as RSRP. Therefore, we apply the proposed machine learning-based prediction toolchain of [57] to estimate P_{TX} and determine the transmission-related power consumption based on laboratory measurements of the device-specific power consumption behavior. Additional details about the applied procedure are presented in [39]. We remark that the power consumption is not a major limiting factor for vehicular crowdsensing. Yet, the usage of battery-powered robotic vehicles such as Unmanned Aerial Vehicles (UAVs) for data acquisition in future Intelligent Transportation Systems (ITSs) is highly being discussed. In addition, the proposed approach might also be applied in intelligent container systems in smart logistics scenarios.

C. Data-driven Network Simulation

It is obvious that the inherently huge effort in performing real world test drives makes this method inappropriate for carrying out large scale parameter studies. Therefore, we exploit the computational efficiency of data-driven analysis methods and implement a DDNS setup according to [28] for the initial parameter tuning phase.

In contrast to classical network simulation methods which simulate the behavior of actual communicating entities and their corresponding protocol stacks, DDNS relies on replaying previously acquired empirical context traces of the targeted deployment scenario. Hereby, the vehicle is virtually moved on its trajectory and the corresponding context information is lookup up from the measurements. For this purpose, we utilize the available open data set of [48]. The simulation of the end-to-end behavior of the transmission schemes is then performed by a combination of machine learning models:

- Based on the available a priori data set, a **deterministic** data rate prediction model — equal to the RF method described in Sec. IV-A — is learned and utilized by the agent to opportunistically schedule the data transmissions. However, due to its deterministic nature, identical feature sets will always result in the same prediction results. Contrastingly, in the real world, the predictions will most likely differ from the ground truth measurements due to imperfections of the prediction model.
- For representing this aspect within the simulation process, a **probabilistic derivation model** is utilized. Through

[2]Source code available at https://github.com/BenSliwa/MTCApp

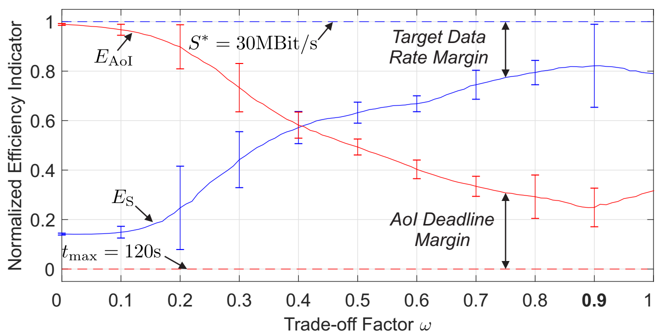


Fig. 12: Trade-off between data rate and AoI optimization for *MNO A* in uplink direction.

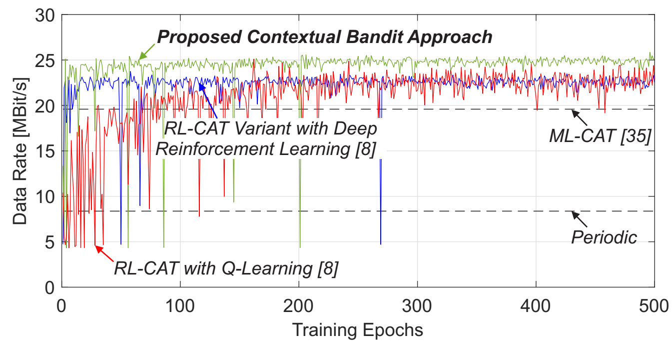


Fig. 13: Convergence behavior of the reinforcement learning-enabled transmission schemes. Each epoch corresponds to a virtual test drive evaluation in the DDNS.

applying GPR on the results of the RF model (for a visual representation of the different models, see Fig. 8), a statistical description of the derivations between predictions and measurements is derived. Furthermore, the Bayesian nature of this model class allows to draw sample values from the learned confidence interval. Within the DDNS simulation, each deterministic prediction $\tilde{S}(t)$ is converted to a sampled *virtual ground truth* value $\hat{S}(\tilde{S}(t))$ which represents the actual resulting data rate of the corresponding data transmission. Further details about this method are presented in [28].

D. Data Analysis

For training the prediction models, we utilize the Lightweight Machine Learning for IoT Systems (LIMITS) framework [58] which allows to automate low-level machine analysis in Waikato Environment for Knowledge Analysis (WEKA) [59] and provides automated export of `C/C++` code of the trained models. In order to generate the GPR models for the DDNS setup and for performing the k-means black spot clustering, the *Statistics and Machine Learning Toolbox* of `MATLAB` is applied.

For analyzing the performance of the machine learning methods, multiple statistical metrics are applied. The *coefficient of determination* R^2 is a statistical metric for the *goodness of fit* of the resulting regression model. It is calculated as

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (\tilde{y}_i - y_i)^2}{\sum_{i=1}^{N} (\bar{y} - y_i)^2} \quad (11)$$

with N as the number of measurements, $\tilde{y}_i$ being the current prediction, y_i being the current measurement, and $\bar{y}$ being the mean value of the measurements.

In addition, we consider Mean Absolute Error (MAE) and RMSE which are calculated as

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

VI. Results

In this section, the results for the DDNS-based optimization phase as well as for the real world performance analysis are presented and discussed. Within the latter, the novel BS-CB method is compared to the existing transmission schemes discussed in Sec. III.

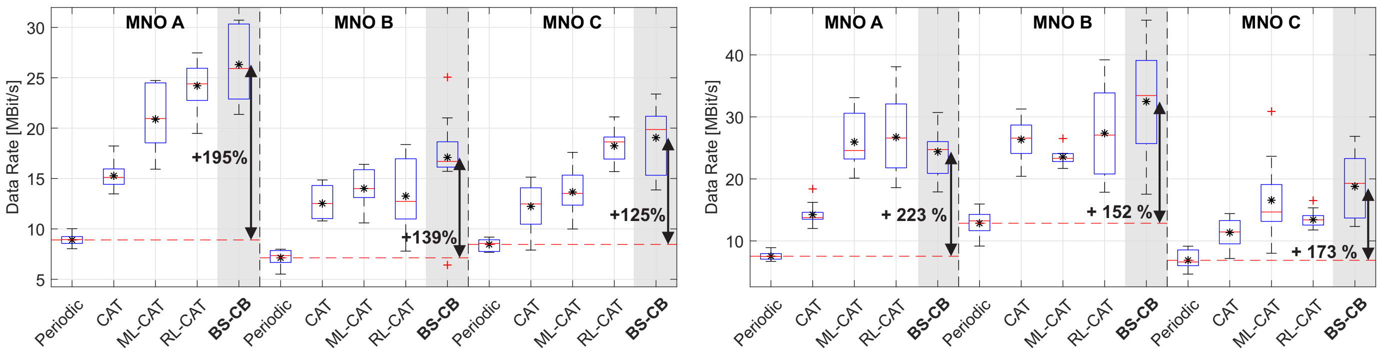
A. DDNS-based Parameter Optimization

As discussed in Sec. IV, opportunistic data transfer is subject to a fundamental trade-off between data rate and AoI optimization: In order to improve the end-to-end data rate, the transmission schemes will rather prefer larger packets which are then transmitted within connectivity hotspots. As a result of the local buffering, the AoI is increased. For the further analysis of this effect, two efficiency indicators are defined:

- The **data rate efficiency** $E_s = \bar{S}/S^*$ is used to analyze how good the average data rate $\bar{S}$ approaches the target data rate S^*.
- The **AoI efficiency** $E_{\mathrm{AoI}} = 1 - \bar{\Delta} t/\Delta t_{\max}$ represents a measure for the margin between the average AoI and the application-specific deadline $\Delta t_{\max}$ of the age of the sensor data.

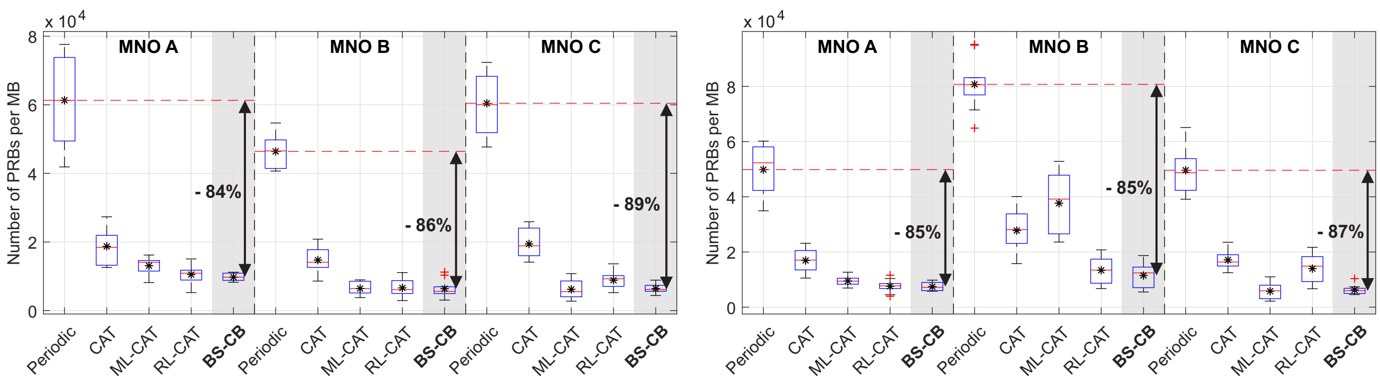
The fundamental trade-off between data rate optimization and AoI optimization which is controlled via the trade-off factor w is shown in Fig. 12. It can be seen that the resulting data rate can be improved by transmitting larger data packets based on a larger value of w. However, this is achieved through a higher buffering time of the acquired sensor data packets which increases the AoI of the data packets. In the following, we focus on data rate optimization and apply $w = 0.9$ within all considered evaluations.

Although the reinforcement learning mechanisms can theoretically be learned online in the field, we apply an offline training approach based on DDNS in order to ensure that the real world evaluations are performed with a converged system. Hereby, we replay previously acquired empirical context traces — which are referred to as *epochs* — and apply the novel reinforcement learning-based transmission schemes. The resulting data rate behavior is shown in Fig. 13. As references, we consider the Q-learning-based RL-CAT and a deep reinforcement learning variant of the latter which applies an ANN configuration according to Sec. IV-A for the data rate prediction. It can be seen that the contextual bandit-based method achieves the highest absolute data rate and reaches a converged system state early after 200 epochs. The remaining



(a) Uplink (b) Downlink

Fig. 14: Comparison of the resulting real world data rate in uplink and downlink direction for the considered transmission schemes and MNOs.



(a) Uplink (b) Downlink

Fig. 15: Comparison of the resulting real world resource efficiency in uplink and downlink direction for the considered transmission schemes and MNOs.

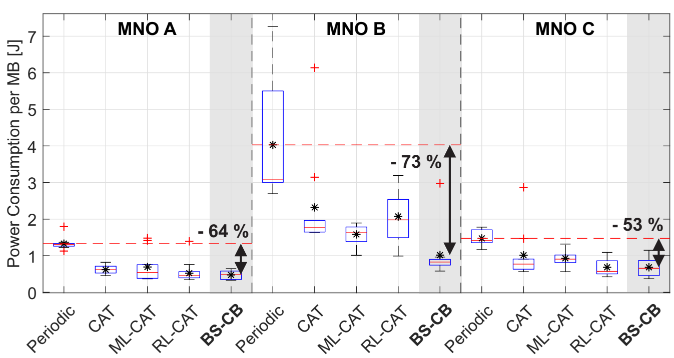


Fig. 16: Transmission-related real world uplink power consumption of the mobile UE.

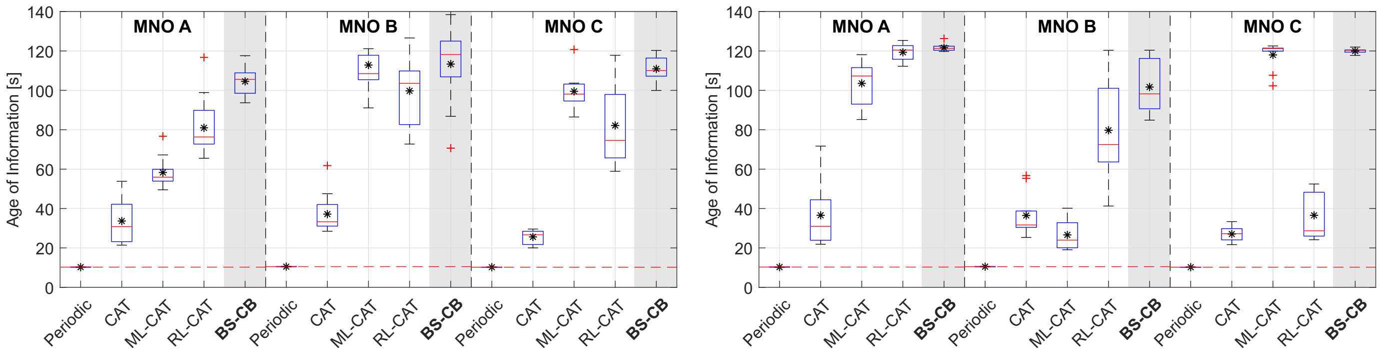
error floor is caused by the imperfections of the data rate prediction model. For RL-CAT, both variants achieve a similar performance level — about 2.5 MBit/s less than BS-CB— of the converged methods. However, it can be seen that the deep reinforcement learning variant achieves a faster convergence behavior than the simple Q-learning approach.

B. Real Wold Performance Comparison

The configured and converged transmission schemes are now applied in a real world evaluation and compared to existing transmission approaches.

The resulting data rate of the different transmission schemes is shown in Fig. 14 for uplink and downlink direction. A clear trend of continuous improvement over the different evolution stages can be observed: Although already the SINR-based CAT method is able to achieve significant improvements in comparison to the periodic data transfer approach, the introduction of the machine learning-based data rate prediction metric by ML-CAT leads to a significant boost which is the result of a more reliable way of accessing the channel behavior. Finally, it can be seen that the reinforcement learning-based decision making outperforms the previously considered heuristic approaches. Hereby, data rate improvements up to 195 % in uplink and up to 223 % in downlink direction are achieved by the proposed BS-CB method. In the downlink, the differences between the opportunistic transmission approaches are less distinct since the downlink performance is more determined by the network congestion than the radio channel conditions [31].

A comparison of the resulting network ressource efficiency



(a) Uplink (b) Downlink

Fig. 17: Comparison of the resulting real world AoI of the sensor data packets.

(represented by the amount of PRBs per transmitted MB) is shown in Fig. 15. It can be seen that all opportunistic data transfer approaches are able to massively reduce — by 84 % to 89 % — the amount of occupied network resources for all MNOs in both transmission directions. One of the main reasons for this behavior is the explicit exploitation of *connectivity hotspot* situations. Here, the robust channel conditions allow to apply higher MCSs for the actual data transfer. Again, it can be seen that the more advanced evolution stages of the CAT approach allow to identify these favorable transmission opportunities in a more reliable way. As a conclusion, the apparently selfish goal of data rate optimization contributes to improving the intra-cell coexistence: Since the limited PRBs are only occupied for small amounts of time, they are freed early and are available for being allocated by other cell users.

The resulting uplink power consumption of the mobile UE is shown in Fig. 16. Since the opportunistic data transmission schemes aim to exploit connectivity hotspots, they implictly increase the average RSRP at the transmission time which is highly correlated to the applied transmission power. As discussed in [57], the latter is the major impact factor for the uplink power consumption since it controls the state of the different power amplifiers of the UE. Therefore, the RSRP optimization leads to a massive improvement of the observed power consumption. Here, BS-CB is able to reduce the latter between -53 % and -73 %. For *MNO B*, it can be observed that the general level of the uplink power consumption is much higher than for the other MNOs. However, this phenomenon is caused by network planning-related aspects of the operator: In the considered evaluation scenario, the average distance to the eNBs is much higher than for the other MNOs. As a consequence of the resulting RSRP reduction — the average RSRP for *MNO B* is -97.64 dBm, -89.61 dBm for *MNO A*, and -88.03 dBm for *MNO C* — the mobile UE applies a higher transmission power to compensate the path loss effects.

Although the considered opportunistic data transfer approaches are able to achieve massive improvements in data rate, network resource efficiency, and uplink power consumption, the price to pay is a significant increase in the AoI of the sensor data packets. Fig. 17 shows a comparison of the resulting AoI values for the different transmission schemes, MNOs, and transmission directions. The plots show

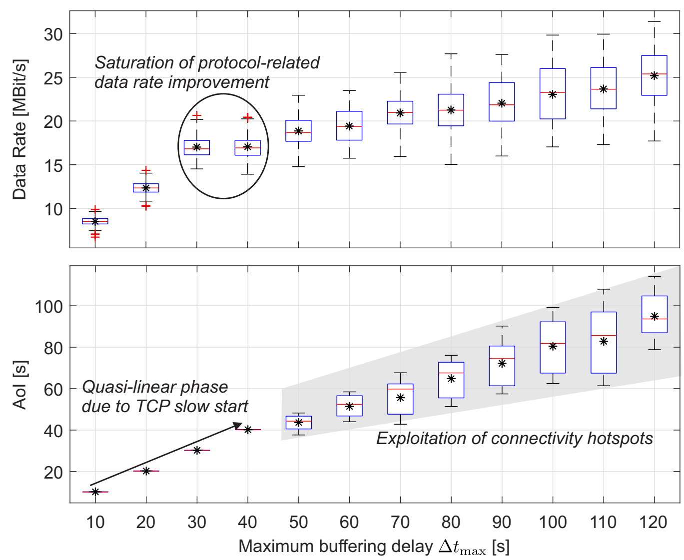


Fig. 18: Impact on the application-specific deadline $\Delta t_{\max}$ on the resulting data rate and AoI.

that this effect is more distinct for the machine learning approaches which detect favorable transmission opportunities more reliably through considering the radio channel quality, protocol-related aspects and partially also the network load. In contrast to that, the highly dynamic behavior of the SINR (see Fig. 2) leads to a higher transmission probability for the regular CAT method which results in a comparably low AoI. However, based on the parameter $\Delta t_{\max}$, the tolerable AoI can be configured with respect to the application requirements. The impact of different values of $\Delta t_{\max}$ on the resulting BS-CB data rate and the AoI of sensor data is shown in Fig. 18. For small values of $\Delta t_{\max}$, a quasi-linear dependency to the latter can be observed. In this phase, the behavior of the transmission scheme is dominated by protocol effects such as TCP slow start. However, a saturation of the data rate improvement is reached at $\Delta t_{\max} = 30$ s. Afterwards, the actual opportunistic behavior starts which exploits the vehicle's mobility behavior for postponing data transmissions to more robust radio channel conditions where a better resource efficiency can be achieved.

As a summary, Fig. 19 shows a spider plot which compares

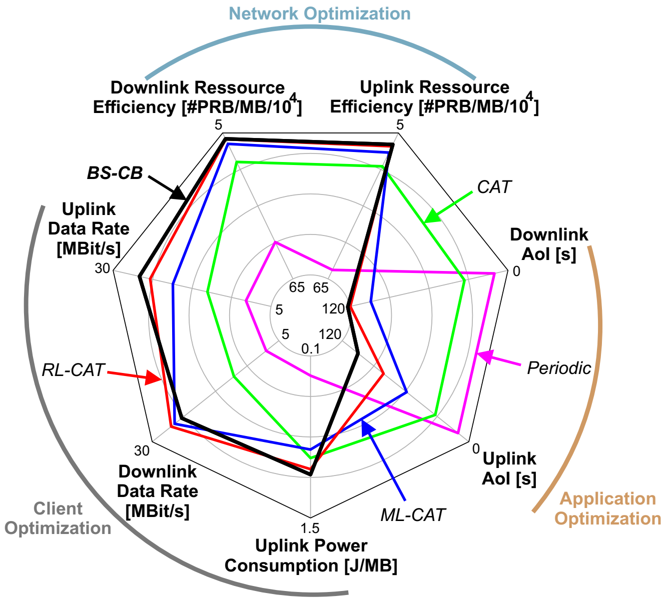


Fig. 19: Summary: Comparison of the average behavior of different performance indicators for the opportunistic data transfer methods in the cellular network of *MNO A*. The axis orientations are chosen such that a large footprint represents a better performance.

the mean results of all considered performance indicators for the different opportunistic data transfer methods in the network of *MNO A*. The axis orientation have been chosen such that a larger footprint corresponds to a better performance. It can be seen that all non-periodic approaches focus on optimizing the network and client domain at the expense of the application domain. Although the proposed BS-CB achieves a slightly better overall performance than RL-CAT, the major differences can be observed between different categories and less between actual transmission schemes: The highest gains are achieved by the hybrid machine learning approaches that utilize data rate prediction and reinforcement learning-based autonomous decision making.

C. Online Learning for Self Adaptation to Concept Drift

The results of the real world performance evaluation have shown that the client-based machine learning-enabled transmission schemes are able to achieve significant improvements in comparison to existing approaches. However, changes in the network (e.g., new resource schedulers in the network infrastructure) might lead to a *concept drift* [60] situation where the interplay of the considered features experiences a significant change. Although the application of reinforcement learning allows to further optimize the autonomous decision making during the live evaluations, the data rate prediction model is trained in a static way and might experience a significant reduction of the prediction accuracy. While it is possible to periodically re-train the prediction model, a better approach is the application of *online learning* in order to enable self adaption to the changed environment conditions. With respect to the edge intelligence classification scheme

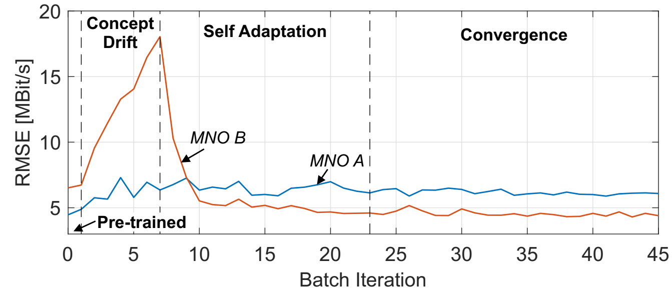


Fig. 20: Self adaption of the data rate prediction model to concept drift: An ANN model is pre-trained on the uplink data of *MNO A* and then incrementally updated with measurements of *MNO B*.

of [54], the integration of online learning would migrate the transmission scheme to *level 6: all on-device* where training and inferencing are run completely locally.

Since it is not possible for us to cause concept drift in the public cellular network, we virtually create a situation where the network behavior spontaneously changes significantly. For this purpose, we pre-train a prediction model on the uplink data set of one MNO and analyze its online adaption to the data set of a different operator. Although online learning variants of RFs exist — e.g., Mondrian Forests [61] — we apply an ANN model for this purpose since this model class inherently supports incremental learning. For the proof-of-concept experiment, a data split is applied: 80 % of the MNO-specific data set $\mathcal{D}$ is used as the training set $\mathcal{D}_{\text{train}}$ and the remaining data forms the test set $\mathcal{D}_{\text{test}}$. Initially, the ANN is pre-trained on the training data of *MNO A*, and then incrementally updated with the training data of *MNO B*. For both operators, the RMSE on the corresponding test sets is analyzed.

The ANN is set up according to Sec. IV-A. For the incremental learning, a minibatch of 32 elements is applied. Hereby, the measurements are buffered locally until the buffer size is equal to 32. Afterwards, the weights of the ANN are updated and the buffer is cleared. The resulting RMSE on the test sets of both network operators is shown in Fig. 20. Four different characteristic phases can be identified:

1) **Pre-trained model**: As the prediction model is initially optimized for being applied in the network of *MNO A*, the prediction accuracy for *MNO A* is significantly higher than for *MNO B*. Still, a certain level of predictability is achieved based on the MNO-independent aspects within the feature set.
2) **Concept drift**: After the first batches of *MNO B* measurements arrive, the prediction model experiences a concept drift: Since the weights of the ANN are neither optimized for *MNO A* nor for *MNO B*, both models suffer from a performance decrease. Hereby, also the MNO-independent features are affected from the changed model weights. This aspect is more dominant for *MNO B* for which only a small amount of measurements has been observed.
3) **Self adaptation**: After seven batch iterations, the ANN

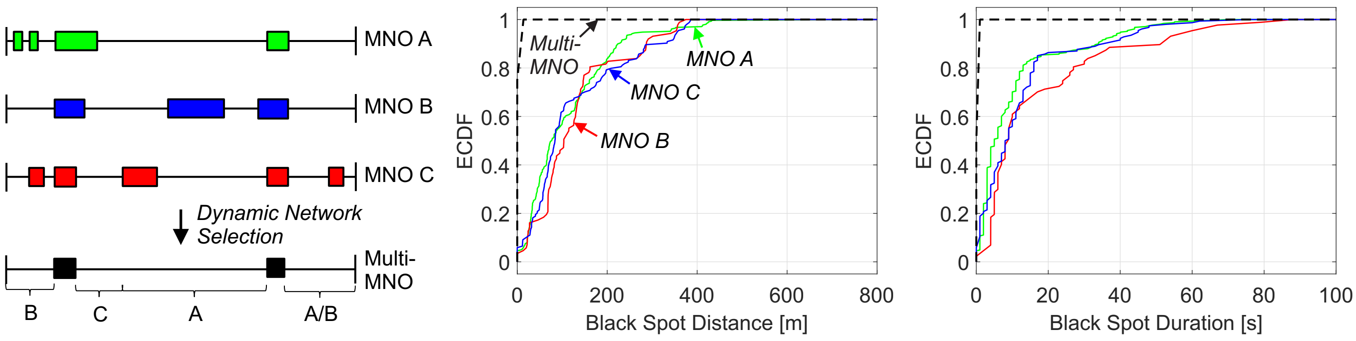


Fig. 21: Compensation of black spot regions through multi-MNO network selection: General solution approach and impact on black spot statistics.

weights start to become optimized for the network of *MNO B*, which results in a steady RMSE improvement for the following iterations.

4) **Convergence**: After around 23 batch iterations, the prediction model reaches a converged state where the RMSE stays at a nearly constant level. In comparison to the pre-trained phase, it can be seen that the RMSE values of the two MNOs have been switched and that the model has successfully adopted itself for *MNO B*.

The considered evaluation shows that online learning allows the data rate prediction model to autonomously adapt to changed network conditions which have a significant impact on the interplay of the features of the prediction model. Within the considered evaluation, even the on-device training time — on average 0.4511 ms per 32-element batch — can be considered negligible. However, the considered ANN model does not reach the accuracy level of the statically trained RF predictor (see Fig. 6). Therefore, future extensions should consider the application of more advanced methods for online learning.

D. Black Spot Statistics and Multi-MNO Transmission Approach

Although the previous discussion has shown that the black spot-aware data transfer approach is able to improve the data rate prediction accuracy as well as the resulting data rate of the BS-CB method, it's usage introduces an additional buffering delay since transmissions are avoided within black spot regions. A possible solution approach for compensating these undesired effects might be the usage of a multi-MNO approach which exploits complementary network infrastructure deployments. Fig. 21 (a) shows a schematic visualization of black spot compensation through application of a multi-MNO approach. If a vehicle encounters a black spot region within its primary network, it dynamically changes the network for performing the sensor data transmissions.

The Empirical Cumulative Distribution Functions (ECDFs) of the times and distances vehicles spend in black spot regions are shown in Fig. 21 (b) and Fig. 21 (c). There are no significant variations between the considered MNOs. In around 50 % of the cases, the black spot regions cover less than 100 m which results in a minor addition to the buffering delay. The usage of a multi-MNO approach leads to massive reductions of both undesired effects. In fact, it is also almost able to compensate the black spot-related effects completely.

VII. Recommendations for Future 6G Networks

Based on the achieved insights, we summarize the our recommendations for using client-based intelligence in future 6G networks as:

- **Non-cellular-centric networking** approaches such as end-edge-cloud orchestrated intelligence allow to exploit the computation and sensing capabilities of the network clients for participating in the overall network optimization. This potential should be recognized by the MNOs and actively supported.
- Data rate prediction allows to make more precise statements about the channel quality than considering raw network quality indicators. Yet, purely client-based prediction methods only have limited insight into the current load of the network. As **cooperative data rate prediction** [51] is able to significantly reduce the end-to-end prediction error, this approach should be explicitly supported by the network infrastructure through actively sharing knowledge about the network load (e.g., obtained from the NWDAF [7]) using dedicated control channel broadcasts.
- Although machine learning has demonstrated its potential in various applications related to wireless network optimization, the sizes of most existing **data sets** are far away from being comparable to the massive data sets used in computer vision by industry giants. Therefore, effort should be taken to acquire data and build up massive open data sets, especially as additional data often leads to larger performance gains than model tuning [49]. A promising initial attempt for sharing data and models is the *machine learning marketplace* proposed in draft recommendation Y.ML-IMT2020-MP of the International Telecommunication Union (ITU).

VIII. Conclusion

In this paper, we proposed BS-CB as a novel method for resource-efficient opportunistic data transmission of vehicular sensor data. BS-CB implements a hybrid machine learning approach which relies on supervised learning for data rate prediction, unsupervised learning for identifying geospatially-dependent uncertainties of the prediction model, and reinforcement learning for autonomously scheduling data transmissions with respect to the anticipated resource efficiency. Within a real world performance evaluation campaign, it was shown that BS-CB is able to achieve massive improvements in comparison to conventional periodic data transmission methods and significantly outperforms existing probabilistic approaches. In future work, we want to analyze more complex online learning approaches such as Mondrian Forest for the data rate prediction. In addition, our research work will focus on further improving the achievable prediction accuracy, e.g., through application of cooperative approaches.

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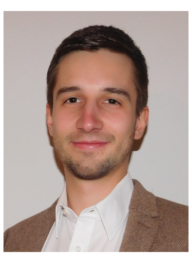

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References

[1] W. Xu, H. Zhou, N. Cheng, F. Lyu, W. Shi, J. Chen, and X. Shen, “Internet of vehicles in big data era,” *IEEE/CAA Journal of Automatica Sinica*, vol. 5, no. 1, pp. 19–35, Jan 2018.

[2] J. Ren, Y. Zhang, K. Zhang, and X. Shen, “Exploiting mobile crowdsourcing for pervasive cloud services: Challenges and solutions,” *IEEE Communications Magazine*, vol. 53, no. 3, pp. 98–105, 2015.

[3] B. Sliwa, T. Liebig, T. Vranken, M. Schreckenberg, and C. Wietfeld, “System-of-systems modeling, analysis and optimization of hybrid vehicular traffic,” in *2019 Annual IEEE International Systems Conference (SysCon)*, Orlando, Florida, USA, Apr 2019.

[4] G. A. Akpakwu, B. J. Silva, G. P. Hancke, and A. M. Abu-Mahfouz, “A survey on 5G networks for the internet of things: Communication technologies and challenges,” *IEEE Access*, vol. 6, pp. 3619–3647, 2018.

[5] A. Capponi, C. Fiandrino, B. Kantarci, L. Foschini, D. Kliazovich, and P. Bouvry, “A survey on mobile crowdsensing systems: Challenges, solutions, and opportunities,” *IEEE Communications Surveys Tutorials*, vol. 21, no. 3, pp. 2419–2465, 2019.

[6] AECC, “White paper: Operational behavior of a high definition map application,” Automotive Edge Computing Consortium, Tech. Rep., May 2020.

[7] 3GPP, “3GPP TS 29.520 - 5G System; Network Data Analytics Services;Stage 3,” 3rd Generation Partnership Project (3GPP), Tech. Rep. 29.520, Mar 2019, version 15.3.0.

[8] P. Yang, Y. Xiao, M. Xiao, and S. Li, “6G wireless communications: Vision and potential techniques,” *IEEE Network*, vol. 33, no. 4, pp. 70–75, July 2019.

[9] S. Ali, W. Saad, N. Rajatheva, K. Chang, D. Steinbach, B. Sliwa, C. Wietfeld, K. Mei, H. Shiri, H. Zepernick, T. M. C. Chu, I. Ahmad, J. Huusko, J. Suutala, S. Bhadauria, V. Bhatia, R. Mitra, S. Amuru, R. Abbas, B. Shao, M. Capobianco, G. Yu, M. Claes, T. Karvonen, M. Chen, M. Girnyk, and H. Malik, “6G white paper on machine learning in wireless communication networks,” Apr 2020.

[10] J. Ren, D. Zhang, S. He, Y. Zhang, and T. Li, “A survey on end-edge-cloud orchestrated network computing paradigms: Transparent computing, mobile edge computing, fog computing, and cloudlet,” *ACM Comput. Surv.*, vol. 52, no. 6, Oct. 2019.

[11] B. Sliwa and C. Wietfeld, “A reinforcement learning approach for efficient opportunistic vehicle-to-cloud data transfer,” in *2020 IEEE Wireless Communications and Networking Conference (WCNC)*, Seoul, South Korea, Apr 2020.

[12] B. Sliwa, R. Adam, and C. Wietfeld, “Acting selfish for the good of all: Contextual bandits for resource-efficient transmission of vehicular sensor data,” in *Proceedings of the ACM MobiHoc Workshop on Cooperative Data Dissemination in Future Vehicular Networks (D2VNet)*, Online, Oct 2020.

[13] J. Wang, C. Jiang, H. Zhang, Y. Ren, K. Chen, and L. Hanzo, “Thirty years of machine learning: The road to pareto-optimal wireless networks,” *IEEE Communications Surveys Tutorials*, pp. 1–1, 2020.

[14] C. Jiang, H. Zhang, Y. Ren, Z. Han, K. C. Chen, and L. Hanzo, “Machine learning paradigms for next-generation wireless networks,” *IEEE Wireless Communications*, vol. 24, no. 2, pp. 98–105, April 2017.

[15] H. Ye, L. Liang, G. Y. Li, J. Kim, L. Lu, and M. Wu, “Machine learning for vehicular networks: Recent advances and application examples,” *IEEE Vehicular Technology Magazine*, vol. 13, no. 2, pp. 94–101, June 2018.

[16] Y. Sun, M. Peng, Y. Zhou, Y. Huang, and S. Mao, “Application of machine learning in wireless networks: Key techniques and open issues,” *IEEE Communications Surveys Tutorials*, vol. 21, no. 4, pp. 3072–3108, 2019.

[17] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 5 2015.

[18] L. Breiman, “Random forests,” *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, Oct. 2001.

[19] C. E. Rasmussen, *Gaussian Processes in Machine Learning*. Berlin, Heidelberg: Springer Berlin Heidelberg, 2004, pp. 63–71.

[20] D. Arthur and S. Vassilvitskii, “k-means++: The advantages of careful seeding,” in *In Proceedings of the 18th Annual ACM-SIAM Symposium on Discrete Algorithms*, 2007.

[21] H. Gacanin, “Autonomous wireless systems with artificial intelligence: A knowledge management perspective,” *IEEE Vehicular Technology Magazine*, pp. 1–1, 2019.

[22] R. S. Sutton and A. G. Barto, *Reinforcement learning: An introduction*, 2nd ed. The MIT Press, 2018.

[23] C. J. C. H. Watkins and P. Dayan, “Q-learning,” *Machine Learning*, vol. 8, no. 3, pp. 279–292, May 1992.

[24] S. Sevgican, M. Turan, K. Gökarslan, H. B. Yilmaz, and T. Tugcu, "Intelligent network data analytics function in 5G cellular networks using machine learning," *Journal of Communications and Networks*, vol. 22, no. 3, pp. 269–280, 2020.

[25] 3GPP, "3GPP TR 23.791 - Study of Enablers for Network Automation for 5G," 3rd Generation Partnership Project (3GPP), Tech. Rep., Jun 2019, v16.2.0.

[26] J. Park, S. Samarakoon, M. Bennis, and M. Debbah, "Wireless network intelligence at the edge," *Proceedings of the IEEE*, vol. 107, no. 11, pp. 2204–2239, Nov 2019.

[27] S. Dörner, S. Cammerer, J. Hoydis, and S. t. Brink, "Deep learning based communication over the air," *IEEE Journal of Selected Topics in Signal Processing*, vol. 12, no. 1, pp. 132–143, Feb 2018.

[28] B. Sliwa and C. Wietfeld, "Data-driven network simulation for performance analysis of anticipatory vehicular communication systems," *IEEE Access*, Nov 2019.

[29] ——, "Towards data-driven simulation of end-to-end network performance indicators," in *2019 IEEE 90th Vehicular Technology Conference (VTC-Fall)*, Honolulu, Hawaii, USA, Sep 2019.

[30] E. R. Cavalcanti, J. A. R. de Souza, M. A. Spohn, R. C. d. M. Gomes, and A. F. B. F. d. Costa, "VANETs' research over the past decade: Overview, credibility, and trends," *SIGCOMM Comput. Commun. Rev.*, vol. 48, no. 2, pp. 31–39, May 2018.

[31] N. Bui, M. Cesana, S. A. Hosseini, Q. Liao, I. Malanchini, and J. Widmer, "A survey of anticipatory mobile networking: Context-based classification, prediction methodologies, and optimization techniques," *IEEE Communications Surveys & Tutorials*, 2017.

[32] S. Toufga, S. Abdellatif, P. Owezarski, T. Villemur, and D. Relizani, "Effective prediction of V2I link lifetime and vehicle's next cell for software defined vehicular networks: A machine learning approach," in *IEEE Vehicular Networking Conference (VNC)*, Los Angeles, USA, Dec 2019.

[33] A. Dalgkitsis, P. Mekikis, A. Antonopoulos, and C. Verikoukis, "Data driven service orchestration for vehicular networks," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–10, 2020.

[34] B. Coll-Perales, J. Gozalvez, and J. L. Maestre, "5G and beyond: Smart devices as part of the network fabric," *IEEE Network*, vol. 33, no. 4, pp. 170–177, July 2019.

[35] S. Ha, S. Sen, C. Joe-Wong, Y. Im, and M. Chiang, "TUBE: Time-dependent pricing for mobile data," in *Proceedings of the ACM SIGCOMM 2012 Conference on Applications, Technologies, Architectures, and Protocols for Computer Communication*, ser. SIGCOMM '12. New York, NY, USA: Association for Computing Machinery, 2012, p. 247–258.

[36] C. Shi, K. Joshi, R. K. Panta, M. H. Ammar, and E. W. Zegura, "CoAST: Collaborative application-aware scheduling of last-mile cellular traffic," in *Proceedings of the 12th Annual International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '14. New York, NY, USA: Association for Computing Machinery, 2014, p. 245–258.

[37] A. Chakraborty, V. Navda, V. N. Padmanabhan, and R. Ramjee, "Coordinating cellular background transfers using loadsense," in *Proceedings of the 19th Annual International Conference on Mobile Computing & Networking*, ser. MobiCom '13. New York, NY, USA: Association for Computing Machinery, 2013, p. 63–74.

[38] J. Lee, J. Lee, Y. Im, S. Dhawaskar Sathyanarayana, P. Rahimzadeh, X. Zhang, M. Hollingsworth, C. Joe-Wong, D. Grunwald, and S. Ha, "CASTLE over the air: Distributed scheduling for cellular data transmissions," in *Proceedings of the 17th Annual International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '19. New York, NY, USA: ACM, 2019, pp. 417–429.

[39] B. Sliwa, R. Falkenberg, T. Liebig, N. Piatkowski, and C. Wietfeld, "Boosting vehicle-to-cloud communication by machine learning-enabled context prediction," *IEEE Transactions on Intelligent Transportation Systems*, Jul 2019.

[40] G. Nikolov, M. Kuhn, A. McGibney, and B.-L. Wenning, "Reduced complexity approach for uplink rate trajectory prediction in mobile networks," in *2020 ISSC, 31st Irish Signals and Systems Conference*, Jun 2020.

[41] J. Lee, S. Lee, J. Lee, S. D. Sathyanarayana, H. Lim, J. Lee, X. Zhu, S. Ramakrishnan, D. Grunwald, K. Lee, and S. Ha, "PERCEIVE: Deep learning-based cellular uplink prediction using real-time scheduling patterns," in *Proceedings of the 18th International Conference on Mobile Systems, Applications, and Services*, ser. MobiSys '20. New York, NY, USA: Association for Computing Machinery, 2020, p. 377–390.

[42] 3GPP, *3GPP TS 36.213 - LTE; Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer procedures (Release 15)*, 3rd Generation Partnership Project Technical Specification, Rev. V15.2.0, Oct 2018.

[43] A. Samba, Y. Busnel, A. Blanc, P. Dooze, and G. Simon, "Instantaneous throughput prediction in cellular networks: Which information is needed?" in *2017 IFIP/IEEE Symposium on Integrated Network and Service Management (IM)*, May 2017, pp. 624–627.

[44] A. Herrera-Garcia, S. Fortes, E. Baena, J. Mendoza, C. Baena, and R. Barco, "Modeling of key quality indicators for end-to-end network management: Preparing for 5G," *IEEE Vehicular Technology Magazine*, vol. 14, no. 4, pp. 76–84, Dec 2019.

[45] J. Riihijarvi and P. Mahonen, "Machine learning for performance prediction in mobile cellular networks," *IEEE Computational Intelligence Magazine*, vol. 13, no. 1, pp. 51–60, Feb 2018.

[46] A. Zappone, M. D. Renzo, and M. Debbah, "Wireless networks design in the era of deep learning: Model-based, AI-based, or both?" *IEEE Communications Magazine*, 2020.

[47] F. Jomrich, A. Herzberger, T. Meuser, B. Richerzhagen, R. Steinmetz, and C. Wille, "Cellular bandwidth prediction for highly automated driving - Evaluation of machine learning approaches based on real-world data," in *Proceedings of the 4th International Conference on Vehicle Technology and Intelligent Transport Systems 2018*, no. 4. SCITEPRESS, Mar 2018, pp. 121–131.

[48] B. Sliwa and C. Wietfeld, "Empirical analysis of client-based network quality prediction in vehicular multi-MNO networks," in *2019 IEEE 90th Vehicular Technology Conference (VTC-Fall)*, Honolulu, Hawaii, USA, Sep 2019.

[49] P. Domingos, "A few useful things to know about machine learning," *Commun. ACM*, vol. 55, no. 10, p. 78–87, Oct. 2012.

[50] M. Akselrod, N. Becker, M. Fidler, and R. Luebben, "4G LTE on the road - what impacts download speeds most?" in *2017 IEEE 86th Vehicular Technology Conference (VTC-Fall)*, Sep. 2017, pp. 1–6.

[51] B. Sliwa, R. Falkenberg, and C. Wietfeld, "Towards cooperative data rate prediction for future mobile and vehicular 6G networks," in *2nd 6G Wireless Summit (6G SUMMIT)*, Levi, Finland, Mar 2020.

[52] C. Ide, B. Dusza, and C. Wietfeld, "Client-based control of the interdependence between LTE MTC and human data traffic in vehicular environments," *IEEE Transactions on Vehicular Technology*, vol. 64, no. 5, pp. 1856–1871, 2015.

[53] B. Sliwa, T. Liebig, R. Falkenberg, J. Pillmann, and C. Wietfeld, "Efficient machine-type communication using multi-metric context-awareness for cars used as mobile sensors in upcoming 5G networks," in *2018 IEEE 87th Vehicular Technology Conference (VTC-Spring)*, Porto, Portugal, Jun 2018, Best student paper award.

[54] Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, and J. Zhang, "Edge intelligence: Paving the last mile of artificial intelligence with edge computing," *Proceedings of the IEEE*, vol. 107, no. 8, pp. 1738–1762, 2019.

[55] L. Li, W. Chu, J. Langford, and R. E. Schapire, "A contextual-bandit approach to personalized news article recommendation," in *Proceedings of the 19th International Conference on World Wide Web*, ser. WWW '10. New York, NY, USA: Association for Computing Machinery, 2010, p. 661–670.

[56] K. Satoda, E. Takahashi, T. Onishi, T. Suzuki, D. Ohta, K. Kobayashi, and T. Murase, "Passive method for estimating available throughput for autonomous off-peak data transfer," *Wireless Communications and Mobile Computing*, vol. 2020, pp. 1–12, 02 2020.

[57] R. Falkenberg, B. Sliwa, N. Piatkowski, and C. Wietfeld, "Machine learning based uplink transmission power prediction for LTE and upcoming 5G networks using passive downlink indicators," in *2018 IEEE 88th Vehicular Technology Conference (VTC-Fall)*, Chicago, USA, Aug 2018.

[58] B. Sliwa, N. Piatkowski, and C. Wietfeld, "LIMITS: Lightweight machine learning for IoT systems with resource limitations," in *2020 IEEE International Conference on Communications (ICC)*, Dublin, Ireland, Jun 2020, Best paper award.

[59] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA data mining software: An update," *SIGKDD Explorations*, vol. 11, no. 1, pp. 10–18, 2009.

[60] J. a. Gama, I. Žliobaite, A. Bifet, M. Pechenizkiy, and A. Bouchachia, "A survey on concept drift adaptation," *ACM Comput. Surv.*, vol. 46, no. 4, Mar. 2014.

[61] B. Lakshminarayanan, D. M. Roy, and Y. W. Teh, "Mondrian forests: Efficient online random forests," in *Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2*, ser. NIPS'14. Cambridge, MA, USA: MIT Press, 2014, p. 3140–3148.