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The Best of Both Worlds: Hybrid Data-Driven and Model-Based Vehicular Network Simulation

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***Abstract*—The analysis of the end-to-end behavior of novel mobile communication methods in concrete evaluation scenarios frequently results in a methodological dilemma: Real world measurement campaigns are highly time-consuming and lack of a controllable environment, the derivation of analytical models is often not possible due to the immense system complexity, system-level network simulations imply simplifications that result in significant derivations to the real world observations. In this paper, we present a hybrid simulation approach which brings together model-based mobility simulation, multi-dimensional Radio Environmental Maps (REMs) for efficient maintenance of radio propagation data, and Data-driven Network Simulation (DDNS) for fast and accurate analysis of the end-to-end behavior of mobile networks. For the validation, we analyze an opportunistic vehicular data transfer use-case and compare the proposed method to real world measurements and a corresponding simulation setup in Network Simulator 3 (ns-3). In comparison to the latter, the proposed method is not only able to better mimic the real world behavior, it also achieves a $\sim$300 times higher computational efficiency.**

I. Introduction

Anticipatory communication [1] has emerged as a novel networking paradigm focusing on *context-aware* optimization of decision processes in highly dynamic wireless communication systems such as vehicular networks. In a recent report [2], the 5G Automotive Association (5GAA) has pointed out that *predictive Quality of Service (QoS)* – e.g., the ability to forecast the achievable data rate along a predicted trajectory – will be one of the key enablers for connected and automated driving. Another recent research trend in this domain is *non-cellular-centric* networking. Hereby, the mobile devices become part of the network fabric and contribute explicitly or implicitly to the overall network optimization [3]. As an example, opportunistic data transfer for delay-tolerant applications (e.g., vehicle-as-a sensor) allows to dynamically schedule data transmissions with respect to the anticipated resource efficiency [4].

However, the development and optimization of these novel mobile networking methods confronts researchers and engineers with a *methodological dilemma*. Real world experiments involve massive efforts and are impacted by an uncontrollable environment. Analytical modeling is often not possible due to the immense complexity of the evaluation scenario. System-level network simulation requires assumptions and simplifications which result in an accuracy degradation for complex real world scenarios (see Sec. II).

In recent work [5], we have presented DDNS as a novel machine learning-enabled method for simulating vehicular communication networks. DDNS learns an end-to-end model of a target Key Performance Indicator (KPI) in a *concrete* scenario based on empirical measurements. The learned model can then be utilized for the performance evaluation of novel methods under study. However, since DDNS relies on replaying real world network conditions as context *traces*, it is bound to the trajectories of the measurements and does not allow to modify the mobility behavior of the vehicles.

In this paper, we bring together the key features of DDNS with *model-based* mobility simulation in order to benefit from the best of both worlds. For this purpose, we decouple the DDNS method from the trace-based approach through usage of multi-dimensional REMs.

The remainder of the paper is structured as follows. After discussing related work in Sec. II, we present the proposed solution approach in Sec. III. Afterwards, the applied methodology is introduced in Sec. IV and finally, the results of the performance evaluation are presented and discussed in Sec. V. The developed simulation framework and the raw results are provided in an Open Source manner[1].

II. Related Work

Network simulation is the de-facto standard method for analyzing the performance of mobile communication systems [6]. System-level simulations provide a controllable environment and allow to compare different methods under study in *abstract* scenarios. However, the achieved results often differ significantly from real measurements in *concrete* complex real world scenarios [5]. The major reasons for this observation are: *Simplifications* such as the usage of probabilistic shadowing models instead of explicit modeling of obstacles and materials. *Assumptions* as concrete parameterizations and applied algorithms are either unknown (e.g., the traffic patterns of the cell users) or are treated confidentially by the Mobile Network Operators (MNOs) (e.g., the applied resource schedulers and concrete parameters of the evolved Node Bs (eNBs)). *Missing features* within the implementation of the network simulator (e.g., as discussed in Sec. IV, Channel Quality Indicator (CQI) and Timing Advance (TA) are not modeled in LTE-EPC Network Simulator (LENA) for ns-3). It can be been these issues are systematically implied for the system-level network simulation method due to the need to *explicitly* model and parameterize communicating entities. In contrast to that,

[1] Source code available at https://github.com/BenSliwa/Hybrid_DDNS

the DDNS method [5] – which is applied in a modified version in this paper – uses machine learning to *implicitly* learn the context-dependent behavior of an observed performance indicator only based on empirical measurements. As an alternative to model-based methods, REMs [7] represent a *data-driven* approach for considering radio propagation effects in wireless network simulations. Hereby, models are replaced by geospatially aggregated radio measurements which are often obtained in a *crowdsensing* manner.

Machine learning has achieved great attention within the wireless research community [8] as its inherent capability of exposing hidden interdependencies between measurable variables allows to derive models for processes which are too complex to describe analytically. In their technical recommendation Y.3172 [9], the International Telecommunication Union (ITU) presents an architectual framework for machine learning-based decision making in future networks. Hereby, a simulation-based *digital twin* of the network allows to safely explore the impact of different decision alternatives before actual actions are performed in the real world *underlay network*. It can be expected that the emerging research field of machine learning-based end-to-end system modeling [10], [5] will further stimulate the progression in this field.

As an example for machine learning-based radio propagation analysis, Thrane et al. [11] propose a model-aided *deep learning* method which implicitly extracts radio propagation characteristics from top-view geographical images. In comparison to ray tracing techniques which are applied in a model of the same evaluation scenario, the machine learning-enabled method is able to reduce the average Reference Signal Received Power (RSRP) prediction error by more than 50 %. However, although deep learning has achieved impressive results in the image processing domain, it is not a universal remedy for all optimization problems in engineering. In the wireless communications domain, the amount of training data is often limited since data has to be acquired in complex measurement campaigns. Due to the *curse of dimensionality* [12], deep learning techniques often get outperformed by simpler models such as Random Forests (RFs) [13] which are able to better cope with smaller data sets (e.g., for mobile data rate prediction as discussed by [5]).

III. Hybrid Data-Driven and Model-Based Vehicular Network Simulation

In this section, the proposed hybrid simulation method and its core modules are introduced. The overall goal is to analyze the performance of a novel *method under study* in a *concrete* real world scenario. As shown in Fig. 1, the proposed approach consists of four core components – the method under study, a model-based mobility simulator, a multi-dimensional REM, and a DDNS setup.

Method under Study: In the following, we illustrate the application of the proposed method based on an example use case focusing on opportunistic vehicular sensor data transmission. For this purpose, we analyze the resulting end-to-end data rate S of different transmission schemes as target KPI.

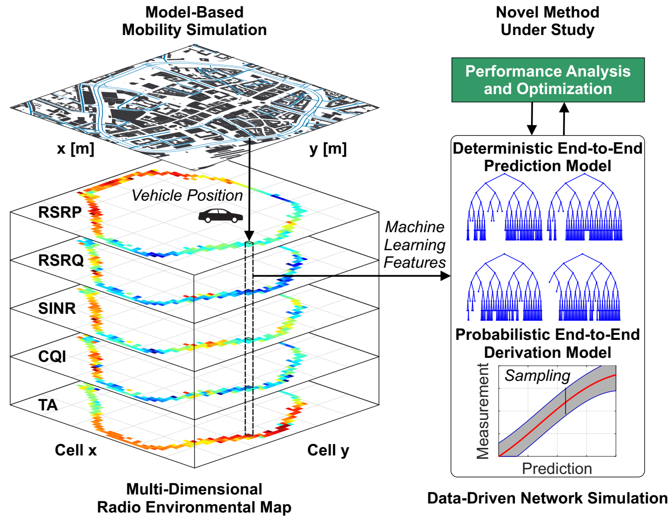


Fig. 1. System architecture model for the proposed hybrid vehicular network simulation method. In the offline training phase, the machine learning models utilize the whole REM data set as a priori information. In the online application phase, predictions are performed based on the looked up values for the corresponding vehicle locations. (Map data: ©OpenStreetMap contributors, CC BY-SA).

Model-based Mobility Simulation: The mobility behavior of the vehicles is represented by a mobility simulation framework which utilizes validated analytical models for the different components such as automatic cruise control and routing. Hereby, the model-based approach allows to analyze the impact of arbitrary traffic conditions and routing paths on the behavior of the method under study. For this purpose, we apply Lightweight ICT-centric Mobility Simulation (LIMoSim) [14] which provides integrated support for real world map data from OpenStreetMap (OSM).

Multi-Dimensional Radio Environmental Map: Within the proposed data-driven simulation approach, radio propagation and protocol effects are implicitly learned by a combination of end-to-end machine learning algorithms. For enabling this data-driven approach, it is assumed that measurement data for the target KPI is available as *a priori information*. This data can either be obtained by performing initial real world measurements, through open data sets such as [15], [11], or via crowdsensing-based services.

For predicting the end-to-end data rate $\tilde{S}$ as the considered target KPI, the User Equipment (UE)-based prediction method from [15] is applied. Multiple features from different logical context domains are considered:

- **Network context**: RSRP, Reference Signal Received Quality (RSRQ), Signal-to-interference-plus-noise Ratio (SINR), CQI, TA
- **Mobility context**: Velocity, Cell id
- **Application context**: Payload size of the packet

While, the features of the mobility and application domains have to be acquired online during the simulations, the network context features are maintained in a multi-dimensional REM whereas each layer corresponds to one of the features for the machine learning process. For a given vehicle position $\mathbf{P}(t)$, the corresponding feature set $\tilde{\mathbf{F}}(t)$ is looked up from the REM

M as

$$\tilde{\mathbf{F}}(t) = M\left(\lfloor\frac{\mathbf{P}(t)}{c}\rfloor\right) \quad (1)$$

with c being the cell width which defines the map granularity.

Data-driven Network Simulation: Finally, the end-to-end behavior of the observed KPI is simulated based on a modified DDNS setup. While conventional DDNS simulations according to [5] are based on replaying context *traces*, the proposed approach utilizes the simulated trajectories and context lookups from the REM. DDNS simulations rely on two main building blocks which are realized as corresponding machine learning models:

- A deterministic **prediction model** is used to learn the end-to-end behavior of the considered indicator using supervised learning on the a priori data set. For the online prediction, the feature set $\tilde{\mathbf{F}}(t)$ is looked up from the REM and the data rate $\tilde{S}(t)$ is predicted as $\tilde{S}(t) = f_{\mathbf{ML}}(\tilde{F}(t))$ using the trained machine learning model $f_{\mathbf{ML}}$. Due to the findings in [15], this model is represented by a RF predictor. However, due to the deterministic nature of the learned model, identical feature sets will always result in identical predictions. In contrast to that, in the real world, the prediction models are imperfect which results in a difference between predictions and ground truth measurements.
- In order to represent this aspect within the simulation setup, a probabilistic **derivation model** is applied for learning the uncertainties of the prediction model of the previous step based on Gaussian Process Regression (GPR) [16]. Hereby, the Bayesian nature of this model class is exploited, since the resulting confidence function allows to sample data values from the whole value range of a given prediction. The sampled value is then utilized as a *virtual ground truth* (e.g., the achieved data rate $S(t)$ of a transmission) within the simulation setup. A visual representation of a derivation model is shown in Fig. 1.

For a more detailed description about the DDNS-specific mechanisms, we forward the interested reader to [5].

IV. Methodology

In this section, the evaluation scenario as well as the tools and methods for the performance evaluation are presented.

A. Evaluation Scenario and Evaluated Methods

For the validation of the proposed approach, we model a vehicle-as-a-sensor use case and compare the end-to-end data rates of different conventional and opportunistic data transmission schemes.

- **Periodic** data transfer with a fixed interval $\Delta t = 10\ s$
- **Channel-aware Transmission (CAT)** [17] is a probabilistic data transfer scheme which derives a transmission probability based on measurements of the current SINR.
- **Machine Learning CAT (ML-CAT)** [4] is a machine-learning-based extension to CAT. Instead of using raw network quality measurements, ML-CAT applies an RF-based data rate prediction which is then used to compute the transmission probability.

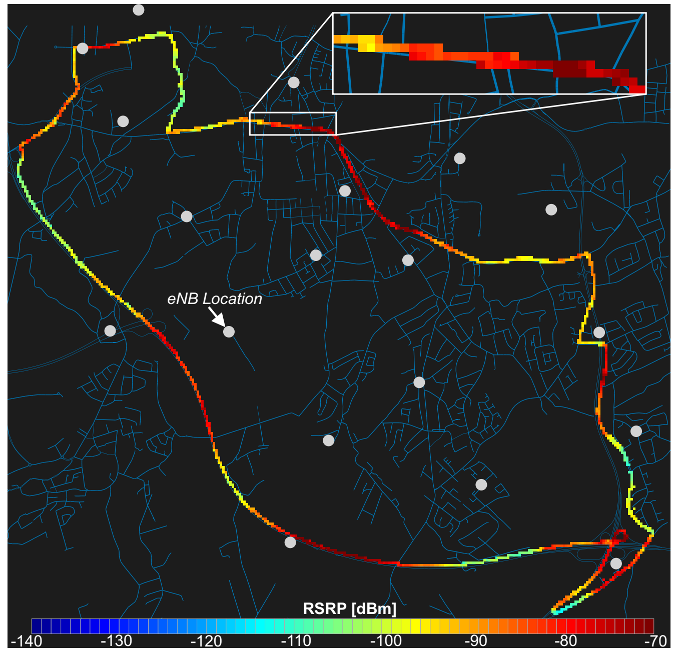


Fig. 2. Overview about the road network topology for the evaluation scenario. The overlay shows the RSRP layer of the REM along the evalation track (Map data: ©OpenStreetMap contributors, CC BY-SA).

Data is transmitted from a moving vehicle in the uplink and downlink direction through the public cellular network using Transmission Control Protocol (TCP). A virtual sensor application generates 50 kByte of data per second which is buffered locally until the transmission decision is made for the whole data buffer. Fig. 2 shows the map of the evaluation scenario as well as the RSRP layer of the REM.

B. Data Analysis

All prediction models are trained with the Open Source Lightweight Machine Learning for IoT Systems (LIMITS) [18] framework which provides high-level automation for validated Waikato Environment for Knowledge Analysis (WEKA) [19] models and supports the generation of `C++` code for trained machine learning models. For the generation of the GPR-based derivation models required for the DDNS, we utilize the *Statistics and Machine Learning Toolbox* of `MATLAB`.

As performance metrics for the resulting prediction errors, we consider Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) which are computed as

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

with $\tilde{y}_i$ being the current prediction, y_i being the current true value, and N being the number of samples.

For all data analysis results, we apply 10-fold cross validation. Based on the findings of related work, the following analyses focuses on using the RF model for performing the

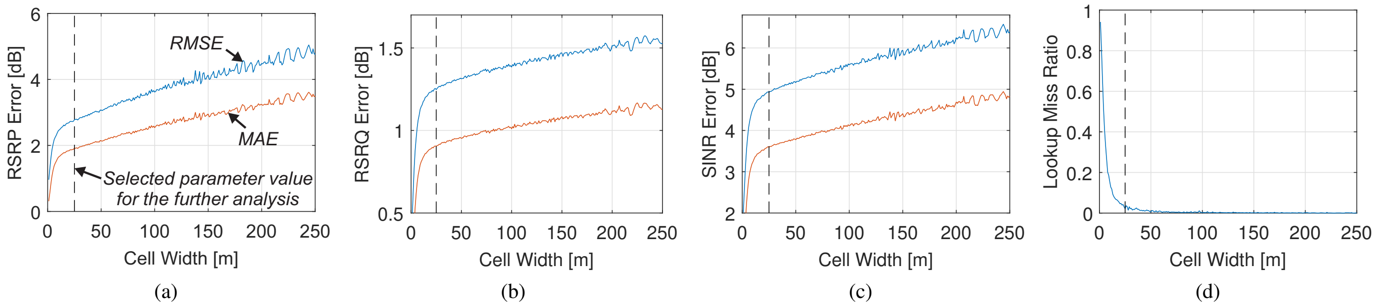


Fig. 3. Impact of the cell width c of the radio environmental map on the resulting lookup accuracy for different network context features.

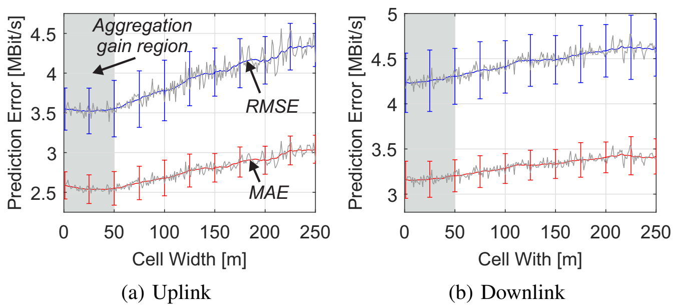


Fig. 4. Impact of the cell width of the radio environmental map on the resulting data rate prediction error. The errorbars show the standard deviation of the 10-fold cross validation.

data rate predictions. A deeper analysis about the performance of different machine learning models can be found in the in-depth study in [5].

C. Reference Discrete Event Simulation Setup in ns-3

For comparison, a classic Discrete Event Simulation (DES)-based setup is created using the Long Term Evolution (LTE) framework LENA [20] for ns-3 [21]. All eNBs are positioned according to their corresponding real world locations. A summary of the simulation parameters is given in Tab. I. However, since LENA is not capable of representing the whole real world feature set – CQI and TA are missing – the prediction models need to be simplified. As a result, the prediction performance is reduced: The average RMSE is increased from 3.9 MBit/s to 4.2 MBit/s.

TABLE I
PARAMETERS OF THE NS-3 SCENARIO

Parameter	Value
Carrier frequency	eNB-specific
Bandwidth	20 MHz
Transmission power P_{TX} (UE)	23 dBm
Transmission power P_{TX} (eNB)	43 dBm
Channel model	HybridBuildingsPropagationLossModel
Number of simulation runs	30

V. RESULTS

In this section, the impact of using REM for modeling radio channel conditions is evaluated. Afterwards, the proposed approach is validated against real world measurements and existing simulation methods.

A. Radio Environmental Maps

Due to the data aggregation performed within the REMs, the obtained values most likely differ from the individual measurements. Therefore, the impact of the aggregation granularity – represented by the cell width c – on the prediction of individual indicators as well as on the overall data rate prediction is investigated.

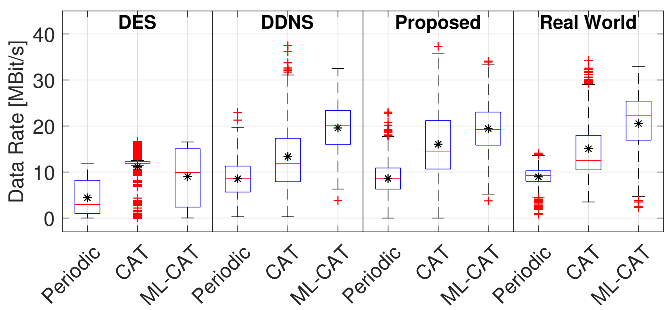
Fig. 3 shows the resulting lookup errors as RMSE and MAE functions for different network context indicators. The highest accuracy is achieved for the smallest c values where most cells only consist of a single measurement. However, in order to allow the usage of REMs within the simulation process, the cell size needs to be large enough to achieve sufficient coverage of the whole evaluation trajectory and minimize the lookup miss ratio which is shown in Fig. 3 (d). Remaining lookup misses can then be compensated by choosing the nearest neighboring cell.

As a direct consequence of these errors, also the machine learning based data rate prediction which uses the network context indicators as features is impacted by the chosen granularity. The resulting data rate prediction error in uplink and downlink direction is shown in Fig. 4. Two different behaviors can be observed. For $c \leq 50\ m$, a slight *aggregation gain* is achieved. In this region, the channel coherence does not change significantly between different measurements in the same cell. Therefore, the REM acts like a filter which compensates short term fluctuations of the different measurements. However, for $c > 50\ m$, the prediction accuracy is reduced for increasing c values as the cell width is too large to represent the local radio propagation characteristics accurately. This effect is more dominant in the uplink than in the downlink direction. As pointed out by the authors of [1], the achievable downlink data rate is mainly determined by the resource competition between different cell users and less sensitive to radio propagation effects.

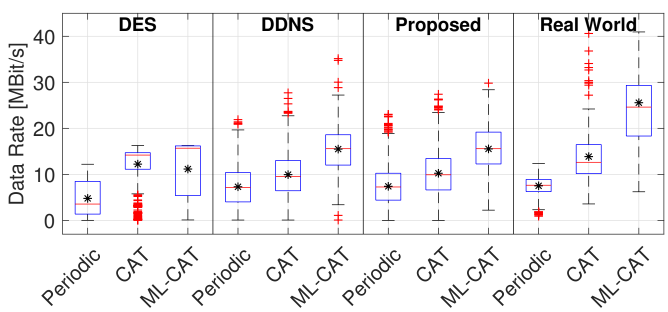
B. Validation

In the following, the proposed hybrid simulation method is compared to trace-based DDNS according to [5], ns-3-based DES, and real world measurements in the same scenario. For all simulation methods, the overall goal is to maximize the congruency with the real world measurements.

The achieved data rate values for the different transmission schemes and performance evaluation methods are shown in

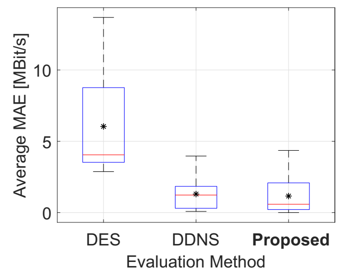


(a) Uplink

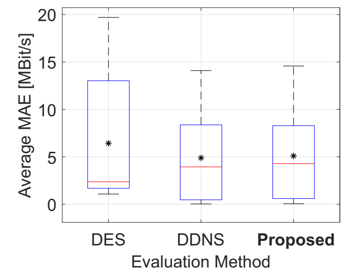


(b) Downlink

Fig. 5. Comparison of the resulting end-to-end behavior of different opportunistic transmission schemes with different evaluation methods.



(a) Uplink



(b) Downlink

Fig. 6. Relative aggregated modeling error for all considered simulation approaches.

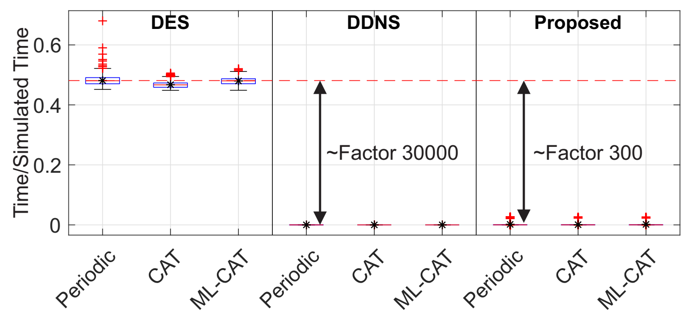


Fig. 7. Comparison of the computational efficiency for the considered performance analysis methods.

Fig. 5. It can be seen that the highest overlap between real world measurements and corresponding simulated behaviors is achieved with the DDNS method and the proposed hybrid simulation method. The simulation-based representation of the real world behavior is more accurate in the uplink than in the downlink direction. As discussed in the previous analysis (see Fig. 4), the machine learning models work more precise in the uplink direction. Here, the end-to-end behavior is more determined by channel related effects which are well covered by the utilized feature set. As analyzed in [22], the downlink data rate prediction accuracy could be significantly improved through consideration of load-depending features such as the number of active users and the amount of occupied Physical Resource Blocks (PRBs). However, as the UEs are not aware of these indicators, it would be required to implement a *cooperative* prediction approach where the eNBs actively distribute this information via control channel announcements. In contrast to the data-driven approaches, the modeling accuracy of the DES setup is significantly lower. Even more problematic, the massive improvements of the ML-CAT method over the CAT method are not represented at all: If the simulation-based performance analysis was used to make a decision for one or the other opportunistic data transmission method, the ns-3-based approach would likely lead to a wrong decision. As all CAT-based methods rely on detecting and exploiting *connectivity hotspots*, they are highly sensitive to the channel conditions. However, the stochastic channel models fail to represent the real world network behavior in the concrete evaluation scenario. In addition, the need to simplify the prediction model for ML-CAT (see Sec. IV-C) due to missing features results in a reduction of the accuracy. The aggregated modeling accuracy for all methods is shown in Fig. 6.

C. Computational Efficiency

In addition to the achievable modeling accuracy, the required time to perform extensive simulation studies is another crucial factor that influences the choice of methods for the performance analysis. A comparison of the computational efficiency of the considered methods is shown in Fig. 7. The highest computational efficiency is achieved with the pure DDNS method which relies on context trace analysis. In comparison to the latter, the proposed hybrid method is impacted by the model-based mobility simulation (e.g., online routing) which reduces the simulation speed by a factor of 100. Still, it is able to benefit from the massive computational efficiency of the machine learning-based network simulation. The classical DES approach represented by ns-3 has the lowest computational efficiency as it requires to explicitly model communicating entities as well as their protocol stacks. For all methods, there are only marginal differences in the computation times of the different transmission schemes.

VI. Conclusion

In this paper, we presented a hybrid approach for simulating the end-to-end performance of vehicular communication systems which brings together model-based mobility simulation, multi-dimensional REMs, and data-driven network simulation. In constrast to existing methods that focus on modeling communicating entities and their corresponding protocol stacks, we utilize a combination of machine learning methods to model the end-to-end behavior of a target KPI. In a comprehensive validation campaign, the proposed method was able to mimic the real world behaviors of different opportunistic data transfer methods more accurately than a reference simulation setup in ns-3. Moreover, the machine learning-enabled approach achieved a massively higher computational efficiency than classical system-level network simulation. As the achievable accuracy of DDNS-enabled simulation approaches is bound by the accuracy of the applied machine learning models, future work will focus on optimizing the latter, e.g., through application of cooperative prediction methods.

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