

# Resource-Efficient Vehicle-to-Cloud Communications Leveraging Machine Learning

Benjamin Sliwa

# **Resource-Efficient Vehicle-to-Cloud Communications Leveraging Machine Learning**

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# Abstract

Vehicular big data is anticipated to become the “new oil” of the automotive industry. Although the novel vehicle-as-a-sensor paradigm will fuel the emergence of innovative crowdsensing-enabled services, the tremendously increased amount of transmitted data represents a massive challenge for the cellular network infrastructure and impacts the intra-cell coexistence of users and services that compete for the limited spectrum resources. More dramatically, due to the complex vehicular radio channel conditions, the mobile devices need to frequently reduce the transmission efficiency in favor of more reliable data transfer, ultimately resulting in a wastage of the limited network resources.

This thesis focuses on the development and analysis of end-edge intelligence mechanisms for delay-tolerant vehicle-to-cloud communications. Taking the predicted end-to-end data rate into account, different opportunistic medium access methods are proposed to achieve a more efficient utilization of the existing network resources. For this purpose, supervised, unsupervised, and reinforcement learning methods are brought together to autonomously detect and exploit favorable transmission opportunities — the so-called connectivity hotspots — by leveraging context knowledge from the network, mobility, and application domains.

For the optimization and the performance evaluation of the novel transmission schemes developed in the scope of this thesis, data-driven network simulation is proposed as a new innovative methodology. Hereby, the combination of deterministic and probabilistic machine learning methods does not only enable close to reality representation of concrete real world evaluation scenarios, it also achieves a massive computational efficiency that is suitable for in-depth optimization of the reinforcement learning schemes. As a bridge for the existing methodological gap between the data analysis and the embedded systems domains, a novel high-level data analysis framework is proposed that builds upon the solid foundation of existing validated low-level model implementations. In addition to providing automatic code generation for the trained machine learning models, the implemented platform-in-the-loop approach allows to precisely assess the final platform-specific resource requirements and enables the determination of the sweet model parameterization for the targeted Internet of Things (IoT) devices ranging from embedded computers up to ultra low power microcontrollers.

The results of this thesis show that machine learning-based data rate prediction models are well able to account for the complex interplay of radio propagation effects, mobility behaviors, and communication protocols. As a result, they provide the fundamental information that allows to autonomously learn resource-efficient data transfer policies. As pointed out in a comprehensive real world performance evaluation of the novel opportunistic data transfer methods,

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the apparently selfish goal of data rate maximization contributes to the good of all and allows to improve the intra-cell coexistence by significantly reducing the resource occupation time as well as the number of network resources per data packet. As a side-effect of the extensive utilization of highly reliable radio channel conditions, the communication-related energy consumption of the mobile device is also significantly improved. By adopting the model parameterization, the trade-off between the achievable benefits and the reduction of the data freshness inherently implied by the opportunistic medium access can be controlled with respect to the application requirements.

In addition to the key research topics, the contributions of this thesis also give an outlook on the enabling function of machine learning for the future network evolution beyond 5G and illustrate its potential to enrich existing scientific methods in the wireless communications domain for end-to-end network simulation and radio propagation modeling.

The thesis was developed during the participation in the German Research Foundation (DFG) Collaborative Research Center (SFB) 876 “Providing Information by Resource-Constrained Analysis”, subproject A4 “Resource Efficient and Distributed Platforms for Integrative Data Analysis” and subproject B4 “Analysis and Communication for Dynamic Traffic Prognosis”.

# Kurzfassung

Aktuelle Vorhersagen prophezeien Big Data als den neuen „Treibstoff“ für die Automobilindustrie. Obwohl durch das neue „Fahrzeug-als-Sensor“ Paradigma die Entstehung einer Vielzahl von neuartigen datengetriebener Diensten vorantreiben wird, stellt der enorme Zuwachs an mobilfunkgestützten Datenübertragungen eine massive Herausforderung für die zellulare Netzinfrastruktur dar und beeinträchtigt die zellinterne Koexistenz von Nutzern und Diensten, welche um die begrenzten Ressourcen des Funkfrequenzspektrums konkurrieren. Dieses Problem erfährt zudem eine weitere Verschärfung, da die komplexen Funkkanaleigenschaften für die fahrzeugbasierte Datenübertragung häufig eine Verringerung der Übertragungseffizienz zugunsten einer erhöhten Übermittlungszuverlässigkeit erfordern, welche letztendlich in einer Verschwendung der begrenzten Ressourcen resultiert.

Die vorliegende Arbeit beschäftigt sich mit der Entwicklung und Analyse von neuartigen Lösungsansätzen zur endgeräteseitigen Nutzung von maschinellen Lernverfahren zur Verbesserung des Übertragungsprozesses für verzögerungstolerante Applikationen. Das zugrundeliegende Gesamtziel liegt hierbei in der effizienteren Nutzung der gegebenen Ressourcen durch einen opportunistischen Kanalzugriff. Für diesen Zweck werden Methoden des überwachten, unüberwachten und des verstärkenden maschinellen Lernens gemeinsam verwendet, um autonom günstige Übertragungsmöglichkeiten — die sogenannten Konnektivitätshotspots — auf Basis von dynamisch erfassten Netzwerk-, Mobilitäts- und Applikationskontextindikatoren zu erkennen und zu nutzen.

Für die Optimierung und die Leistungsbewertung der neuen Übertragungsverfahren wird die datengetriebene Netzwerksimulation als neue innovative Methodik vorgestellt, welche eine realitätsgetreue Verhaltensanalyse neuer Kommunikationsverfahren in virtuellen Abbildern realer Evaluationsszenarien ermöglicht. Durch die enorme Recheneffizienz, welche durch eine Kombination verschiedener maschineller Lernverfahren erzielt wird, können die neuartigen Verfahren zur autonomen Entscheidungsfindung effizient in realistischen virtuellen Netzwerkumgebungen trainiert werden. Als Brücke zur Schließung der methodischen Lücke zwischen den Forschungsfeldern der Datenanalyse und der eingebetteten Systeme, wird ein neuer Lösungsansatz vorgestellt, welcher eine zielgerichtete Automatisierung von Datenanalysen auf Basis von validierten Modellimplementierungen ermöglicht. Zusätzlich zur automatischen Generierung von Quellcode für die trainierten Prädiktionsmodelle, erlaubt die explizite Einbeziehung der Eigenschaften und Beschränkungen der Zielplattform, den resultierenden Ressourcenbedarf präzise zu bestimmen und plattformspezifische Parametrisierungen der Modelle vorzunehmen.

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Die Ergebnisse dieser Arbeit belegen, dass maschinelle Lernverfahren imstande sind, das komplexe Zusammenspiel von Funkausbreitungseigenschaften, Mobilitätsverhalten und Kommunikationsprotokollen in ein geschlossenes Modell zur Vorhersage der erzielbaren Datenrate zu überführen. Dieses stellt fundamentale Informationen zur Einschätzung der Güte der Datenübertragung bereit und ermöglicht das eigenständige Lernen von Entscheidungsrichtlinien zur ressourcenefizienten Datenübertragung. Wie in einer umfassenden experimentellen Evaluationskampagne der neuen opportunistischen Übertragungsmethoden gezeigt wird, trägt das scheinbar eigennützige Ziel der Datenratenmaximierung zum Wohle aller bei und verbessert die Intrazellkoexistenz durch eine signifikante Reduzierung der notwendigen Zellressourcen pro Datenpaket. Als Nebeneffekt führt die umfangreiche Ausnutzung hochzuverlässiger Funkkanalsituationen zudem zu einer starken Verbesserung des kommunikationsbezogenen Energieverbrauchs des mobilen Endgeräts. Durch Anpassung der Modellparameter kann ein Kompromiss zwischen den erzielbaren Verbesserungen und der durch den opportunistischen Kanalzugriff implizierten Reduzierung der Aktualität der übertragenen Daten auf Basis der Applikationsanforderungen eingestellt werden.

Zusätzlich zu den Kernforschungsfragen ermöglichen die im Kontext dieser Arbeit entstandenen Forschungsbeiträge einen Ausblick auf die Schlüsselfunktion maschineller Lernverfahren für die zukünftige Netzevolution über 5G hinaus und veranschaulichen das diesen Ansätzen innenliegende Potenzial zur Verbesserung existierender wissenschaftlicher Methoden, wie z.B. zur Ende-zu-Ende Netzwerksimulation und für die Modellierung von Funkausbreitungseigenschaften.

Die Arbeit ist im Rahmen der Mitarbeit im Sonderforschungsbereich (SFB) 876 „Verfügbarkeit von Information durch Analyse unter Ressourcenbeschränkung“, Teilprojekt A4 „Ressourcen-effiziente und verteilte Plattformen zur integrativen Datenanalyse“ und Teilprojekt B4 „Analyse und Kommunikation für die dynamische Verkehrsprognose“ der Deutschen Forschungsgemeinschaft (DFG) entstanden.

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## List of Acronyms

|                     |                                                               |
|---------------------|---------------------------------------------------------------|
| <b>3GPP</b>         | 3rd Generation Partnership Project                            |
| <b>5GAA</b>         | 5G Automotive Association                                     |
| <b>AECC</b>         | Automotive Edge Computing Consortium                          |
| <b>AMC</b>          | Adaptive Modulation and Coding                                |
| <b>ANN</b>          | Artificial Neural Network                                     |
| <b>AODV</b>         | Ad-hoc On-demand Distance Vector                              |
| <b>AoI</b>          | Age of Information                                            |
| <b>API</b>          | Application Programming Interface                             |
| <b>ARIMA</b>        | Autoregressive Integrated Moving Average                      |
| <b>ARQ</b>          | Automatic Repeat reQuest                                      |
| <b>ASU</b>          | Arbitrary Strength Unit                                       |
| <b>B.A.T.M.A.N.</b> | Better Approach To Mobile Ad-hoc Networking                   |
| <b>BLER</b>         | Block Error Rate                                              |
| <b>BS-CB</b>        | Black Spot-Aware Contextual Bandit                            |
| <b>BS-pCB</b>       | Black Spot-Aware Predictive Contextual Bandit                 |
| <b>C-V2X</b>        | Cellular V2X                                                  |
| <b>CAGR</b>         | Compound Annual Growth Rate                                   |
| <b>CAM</b>          | Cooperative Awareness Message                                 |
| <b>CAN</b>          | Controller Area Network                                       |
| <b>CART</b>         | Classification And Regression Tree                            |
| <b>CASTLE</b>       | Client-side Adaptive Scheduler That minimizes Load and Energy |
| <b>CAT</b>          | Channel-aware Transmission                                    |
| <b>Cat-M</b>        | Category M                                                    |
| <b>CBR</b>          | Constant Bitrate                                              |

|                |                                                                          |
|----------------|--------------------------------------------------------------------------|
| <b>CLAW</b>    | Cellular Link-Aware Web loading                                          |
| <b>CLI</b>     | Command Line Interface                                                   |
| <b>CN</b>      | Core Network                                                             |
| <b>CoAST</b>   | Collaborative Application-Aware Scheduling of Last Mile Cellular Traffic |
| <b>CoPoMo</b>  | Context-aware Power Consumption Model                                    |
| <b>CPS</b>     | Cyber-Physical System                                                    |
| <b>CPU</b>     | Central Processing Unit                                                  |
| <b>CQI</b>     | Channel Quality Indicator                                                |
| <b>CRS</b>     | Cell Specific Reference Signal                                           |
| <b>CSI-RS</b>  | Channel State Information Reference Signal                               |
| <b>CUSCUS</b>  | CommUnicationS-Control distribUted Simulator                             |
| <b>D2D</b>     | Device-to-Device                                                         |
| <b>DBSCAN</b>  | Density-Based Spatial Clustering of Applications with Noise              |
| <b>DCI</b>     | Downlink Control Information                                             |
| <b>DDNS</b>    | Data-Driven Network Simulation                                           |
| <b>DES</b>     | Discrete Event Simulation                                                |
| <b>DFT</b>     | Discrete Fourier Transform                                               |
| <b>DL</b>      | Downlink                                                                 |
| <b>DSRC</b>    | Dedicated Short Range Communication                                      |
| <b>ECDF</b>    | Empirical Cumulative Distribution Function                               |
| <b>EDR</b>     | Event Data Recorder                                                      |
| <b>eMBB</b>    | enhanced Mobile Broadband                                                |
| <b>eNB</b>     | evolved Node B                                                           |
| <b>EPC</b>     | Evolved Packet Core                                                      |
| <b>EPS</b>     | Encapsulated Postscript                                                  |
| <b>ESP-IDF</b> | Espressif IoT Development Framework                                      |
| <b>E-UTRAN</b> | Evolved UMTS Terrestrial Radio Access Network                            |
| <b>EVA</b>     | Extended Vehicular A                                                     |

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**FALCON** Fast Analysis of LTE Control channels

**FANET** Flying Ad-hoc Network

**FG-ML5G** Focus Group on Machine Learning for Future Networks Including 5G

**FG-NET-2030** Focus Group on Technologies for Network 2030

**FPC** Fractional Path Loss Compensation

**GAN** Generative Adversarial Network

**gNB** Next Generation Node B

**GNSS** Global Navigation Satellite System

**GPR** Gaussian Process Regression

**GPS** Global Positioning System

**GPSR** Greedy Perimeter Stateless Routing

**H2H** Human-to-Human

**HARQ** Hybrid ARQ

**HAS** HTTP Adaptive Streaming

**HD** High Definition

**HLA** High Level Architecture

**HMM** Hidden Markov Model

**IDE** Integrated Development Environment

**IDM** Intelligent Driver Model

**IoT** Internet of Things

**IoV** Internet of Vehicles

**IPC** Interprocess Communication

**IQN** In-advance QoS Notification

**ITS** Intelligent Transportation System

**ITU** International Telecommunication Union

**ITU-T** ITU Telecommunication Standardization Sector

**JNI** Java Native Interface

**KNIME** Konstanz Information Miner

**KPI** Key Performance Indicator

|                |                                              |
|----------------|----------------------------------------------|
| <b>LET</b>     | Link Expiry Time                             |
| <b>LIDAR</b>   | Light Detection And Ranging                  |
| <b>LIMITS</b>  | LIghtweight Machine learning for IoT Systems |
| <b>LIMoSim</b> | LIghtweight ICT-centric Mobility Simulation  |
| <b>LinUCB</b>  | Linear Upper Confidence Bound                |
| <b>LOS</b>     | Line-of-Sight                                |
| <b>LSTM</b>    | Long Short-term Memory                       |
| <b>LTE</b>     | Long Term Evolution                          |
| <b>M2M</b>     | Machine-to-Machine                           |
| <b>M5</b>      | M5 Regression Tree                           |
| <b>MAC</b>     | Medium Access Control                        |
| <b>MAE</b>     | Mean Absolute Error                          |
| <b>MANET</b>   | Mobile Ad-hoc Network                        |
| <b>MCN</b>     | Multi-hop Cellular Network                   |
| <b>MCS</b>     | Modulation and Coding Scheme                 |
| <b>MCU</b>     | Microcontroller Unit                         |
| <b>MDI</b>     | Mean Decrease Impurity                       |
| <b>MDP</b>     | Markov Decision Process                      |
| <b>ML-CAT</b>  | Machine Learning CAT                         |
| <b>ML-pCAT</b> | Machine Learning pCAT                        |
| <b>mMTC</b>    | massive Machine Type Communication           |
| <b>mmWave</b>  | millimeter Wave                              |
| <b>MNO</b>     | Mobile Network Operator                      |
| <b>MSS</b>     | Maximum Segment Size                         |
| <b>MTC</b>     | Machine Type Communication                   |
| <b>MTU</b>     | Maximum Transmission Unit                    |
| <b>NB-IoT</b>  | Narrowband IoT                               |
| <b>NDK</b>     | Native Development Kit                       |
| <b>NLOS</b>    | Non-Line-of-Sight                            |

---

**NR** New Radio

**ns-3** network simulator 3

**NSA** Non-standalone

**NWDAF** Network Data Analytics Function

**OEM** Original Equipment Manufacturer

**OFDM** Orthogonal Frequency Division Multiplexing

**OFDMA** Orthogonal Frequency Division Multiple Access

**OLSR** Optimized Link State Routing

**OMNeT++** Objective Modular Network Testbed in C++

**OpenGL** Open Graphics Library

**OSM** OpenStreetMap

**OTA** Over-the-Air

**OWL** Online Watcher for LTE

**PAPR** Peak-to-Average Power Ratio

**PARRoT** Predictive Ad-hoc Routing fueled by Reinforcement learning and Trajectory knowledge

**pCAT** predictive CAT

**PERCEIVE** Predicted pERformance by CEllular Inferring deVice

**PDCCH** Physical Downlink Control Channel

**PDCP** Packet Data Convergence Protocol

**PDR** Packet Delivery Ratio

**PRB** Physical Resource Block

**QAM** Quadrature Amplitude Modulation

**QoS** Quality of Service

**QPSK** Quadrature Phase Shift Keying

**QxDM** Qualcomm eXtensible Diagnostic Monitor

**RAIK** Regional Analysis to Infer KPIs

**RADAR** Radio Detection and Ranging

**RAM** Random Access Memory

|                |                                                   |
|----------------|---------------------------------------------------|
| <b>RAN</b>     | Radio Access Network                              |
| <b>RAT</b>     | Radio Access Technology                           |
| <b>RB</b>      | Resource Block                                    |
| <b>RBF</b>     | Radial Basis Function                             |
| <b>REM</b>     | Radio Environmental Map                           |
| <b>RF</b>      | Random Forest                                     |
| <b>RIS</b>     | Reconfigurable Intelligent Surface                |
| <b>RL-CAT</b>  | Reinforcement Learning CAT                        |
| <b>RL-pCAT</b> | Reinforcement Learning pCAT                       |
| <b>RLC</b>     | Radio Link Control                                |
| <b>RMSE</b>    | Root Mean Square Error                            |
| <b>RNTI</b>    | Radio Network Temporary Identifier                |
| <b>RoI</b>     | Region of Interest                                |
| <b>RSRP</b>    | Reference Signal Received Power                   |
| <b>RSRQ</b>    | Reference Signal Received Quality                 |
| <b>RSSI</b>    | Received Signal Strength Indicator                |
| <b>RSU</b>     | Roadside Unit                                     |
| <b>RTT</b>     | Round-trip Time                                   |
| <b>SA</b>      | Standalone                                        |
| <b>SC</b>      | Subcarrier                                        |
| <b>SC-FDMA</b> | Single Carrier Frequency Division Multiple Access |
| <b>SDR</b>     | Software-defined Radio                            |
| <b>SEQ</b>     | Sequence Number                                   |
| <b>SINR</b>    | Signal-to-Interference-Plus-Noise Ratio           |
| <b>SNR</b>     | Signal-to-noise Ratio                             |
| <b>SMO</b>     | Sequential Minimal Optimization                   |
| <b>SPS</b>     | Semi-persistent Scheduling                        |
| <b>SS</b>      | Signal Strength                                   |
| <b>SUMO</b>    | Simulation of urban mobility                      |

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**SVM** Support Vector Machine  
**TA** Timing Advance  
**TBS** Transport Block Size  
**TCP** Transmission Control Protocol  
**TPC** Transmission Power Control  
**TRUST** Throuput Prediction based on LSTM  
**TTI** Transmission Time Interval  
**TTL** Time to Live  
**TUBE** Time-dependent Usage-based Broadband price Engineering  
**UART** Universal Asynchronous Receiver Transmitter  
**UAV** Unmanned Aerial Vehicle  
**UCB** Upper Confidence Bound  
**UDP** User Datagram Protocol  
**UE** User Equipment  
**UI** User Interface  
**UL** Uplink  
**UMa** Urban Macrocell  
**URLLC** Ultra-Reliable Low Latency Communication  
**USD** US-Dollar  
**V2X** Vehicle-to-Everything  
**VANET** Vehicular Ad-hoc Network  
**Veins** Vehicles in Network Simulation  
**WAVE** Wireless Access in Vehicular Environments  
**WCET** Worst Case Execution Time  
**WEKA** Waikato Environment for Knowledge Analysis  
**WGS84** World Geodetic System 1984  
**WLAN** Wireless Local Area Network  
**WSN** Wireless Sensor Network  
**XAI** Explainable Artificial Intelligence