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Data-Driven Energy Profiling for Resource-Efficient 5G Vertical Services

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***Abstract*—Energy efficiency is a major concern in the development of future mobile networks. Besides the infrastructure, a significant challenge is the power consumption of the user equipment, as it directly affects the quality of experience. We have conducted comprehensive laboratory measurements on the latest commercial 5G devices to assess power consumption, considering different frequencies, bandwidths and duplex patterns. A key result is the non-linear increase in power consumption with uplink transmit power. An empirical model with machine learning methods is proposed to enable quantitative analysis of the power consumption based on the communication behavior. By applying this model to an extensive data set, spatiotemporal predictions of real-world user equipment power consumption were performed. Depending on the deployment location and communication behavior, battery life can be as much as five times lower. These results can be utilized to perform energy-aware scheduling and deployment site selection to enhance the energy footprint of mobile platforms and Internet of Things devices.**

I. Introduction

Power consumption is becoming increasingly important and costly in the context of climate change. Recently, 5G mobile network power consumption reduction has been a significant research direction and further optimizations in future releases are forthcoming [1–3]. User Equipment (UE) power consumption, in particular, is critical for the battery life of mobile network users and directly affects the quality of experience. A lower power consumption improves sustainability, as charging or changing batteries becomes less frequent, and energy harvesting approaches become more feasible. For Narrowband Internet of Things (NB-IoT) devices, UE power consumption has been noticed to rise by a factor of over three due to decreased transmit power of base stations, drastically reducing the expected battery life [4]. That shows the influence of the signal strength on user device battery life and potential contrary and complementary aspects of green networking. In the context of a rapidly increasing number of mobile subscribers and a swift rise in 5G capable UEs [5], changes in the power consumption of user devices have a major leverage effect.

In this paper, we are measuring the energy consumption of 5G devices under different configurations to deduce an empirical power consumption model, which can be applied to assess real-world power consumption. Machine learning is utilized to predict model parameters like the uplink transmit power. As illustrated in Fig. 1, it varies strongly with context parameters like the location, affecting the present wireless channel. A specific energy efficiency per bit is reached based on the transmit power and the achieved channel data rate. This efficiency can be degraded severely in poorly covered areas, affecting UE battery life. Our model allows to avoid these areas and thus reduce power consumption.

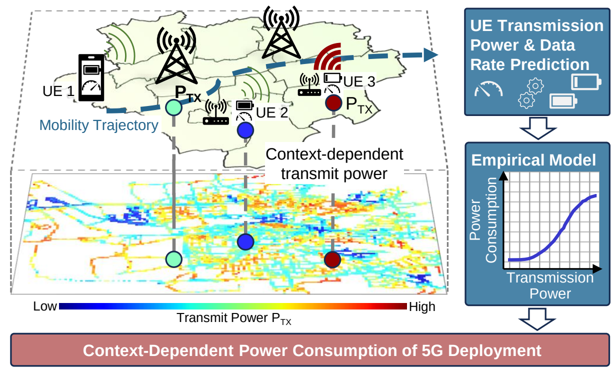


Fig. 1. User equipment (UE) power consumption resulting in different battery life at given locations in smart city IoT deployments.

The remainder of the paper is structured as follows: After discussing the related work in Sec. II, our approach to predict UE power consumption is introduced in Sec. III, followed by an overview of the methodological aspects in Sec. IV. Finally, detailed results about the measured power consumption under different scenarios and implications to real-world services are provided in Sec. V.

II. Related Work

A critical factor for UE energy consumption is the utilized uplink transmit power of the UE. The power control of 5G networks for the Physical Uplink Shared Channel (PUSCH) can be described by Eqn. 1 [6].

$$P_{\text{PUSCH}} = min \begin{cases} P_{\text{gNB, max}} \\ P_{\text{TX, max}} \\ P_{0,\text{TX}} + 10 \cdot log(2^{\mu} \cdot N_{\text{PRB}}) + \\ \quad \alpha_{\text{frac}} \cdot P_{\text{loss}} + \Delta_{\text{MCS}} + f_{\text{TPC}} \end{cases} \tag{1}$$

While the transmit power of the UE is bound by $P_{\text{TX, max}}$, a cell-specific maximum uplink power $P_{\text{gNB, max}}$ can be configured too. P_{PUSCH} is otherwise calculated as the sum of the nominal UE transmit power $P_{0,\text{TX}}$ and further context-dependent factors. These include the current bandwidth (expressed by the number of utilized Physical Resource Blocks (PRBs) and the sub-carrier spacing μ), and the path loss P_{Loss}. The factor α_{frac} represents a fractional power control multiplier

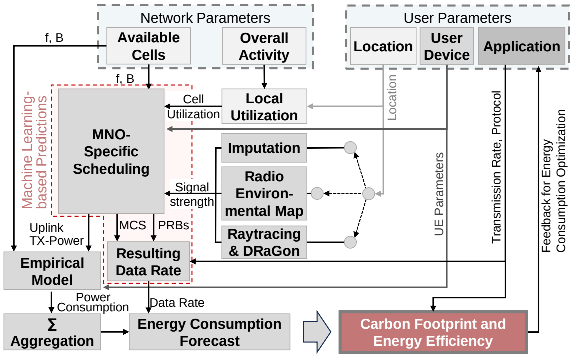


Fig. 2. System parameters and dependencies for machine learning-based power consumption modeling of real-world 5G mobile networks.

Fig. 3. Laboratory setup to evaluate user equipment power consumption.

enabling 5G networks to only partly compensate the path loss, reducing inter-cell interference [7]. If the Modulation and Coding Scheme (MCS) is changed while the channel remains constant, the transmit power must be adapted by Δ_{MCS} to account for the changed Signal-To-Interference-Plus-Noise-Ratio (SINR) requirements. The factor f_{TPC} is used for closed-loop power control with the help of Transmit Power Control (TPC) commands from the Next Generation Node B (gNB), fine-tuning UE transmit power [7].

In [8], a Context-Aware Power Consumption Model (CoPoMo) for LTE is introduced, enabling energy consumption prediction for 4G UEs based on system and context parameters. One main result was the non-linear relationship between the UE transmit power and the resulting UE energy consumption. That led to important findings on power consumption: UE battery life can be enhanced by scheduling and efficiently utilizing carrier aggregation [9].

III. Proposed Hybrid Machine Learning Approach

In this work, the location, device type and the utilized service profile are assumed to be given. As shown in Fig. 2, these define the needed transmit rate. A tuple of granted PRBs, an MCS, and a suitable transmit power may be selected based on multiple cell parameters, resulting in a set data rate. The transmit power directly affects the power consumption of the UE, replicated by an empirical model similar to as proposed in [8]. By utilizing the forecast of this model as feedback, application parameters may be changed to comply with power consumption requirements, or a more suitable deployment location can be chosen. Radio Environmental Maps (REMs), as a part of a mobile network digital twin, can be used to depict real-world signal strength [10]. If no data is available at some locations, raytracing or machine learning-based approaches like `DRaGon` [11] or imputation methods could be utilized. The scheduling of PRBs, MCSs and transmit power to UEs are of crucial importance to the power consumption. In contrast to a classical approach, these parameters are not assumed to be given as input parameters. Instead, they are predicted using machine learning to reflect real-world characteristics more accurately.

IV. Methodology

A reproducible measurement setup is crucial for the systematic evaluation of UE power consumption. Our laboratory setup is based on a 5G radio communication tester, which is used to emulate a freely configurable gNB. An *iperf* server is hosted on this device for User Datagram Protocol (UDP) uplink data rate measurements to accurately replicate the impact of uplink data transmits on the power consumption. The hardware ports of the tester are configured so that uplink and downlink signals are divided between two connectors. Via a circulator and a signal splitter, a modem is connected transparently to the split of the signal. Two different modems were used for the measurements. Only the respective primary antenna of both modems was connected, while the others were terminated to decrease complexity. The modems are powered with 3.3 V directly by a power supply with an integrated power meter. A spectrum analyzer is connected to the uplink path to verify the set uplink power.

These measurement devices are controlled by an Accelerated Processing Unit (APU) via a local network. With the help of an application programming interface, mobile network cells are set up and started automatically. The APU then connects the modem to the emulated 5G cell using *AT* commands and the *ModemManager*. Finally, an uplink data rate measurement is initiated before the power consumption and spectrum analyzer measurements are triggered. After each measurement, the modem is disconnected from the gNB to change settings. This fully automated setup enables us to repeat measurements and change measurement scenarios in a reproducible and fast way. In Tab. I, the parameters of the setup are listed, with the bold-printed parameters being used unless otherwise noted.

V. Laboratory Power Consumption Measurement and Real-World Prediction

With the help of the laboratory setup described in Sec. III, multiple scenarios were evaluated. These include the variation of the UE uplink transmit power P_{TX}, the bandwidth B,

TABLE I
Parameters of the Laboratory Measurement Setup

Parameter	Value
Technologies	4G, 5G NSA and **5G SA**
User Devices	RM500Q-GL, **RM520N-EU**
Antenna Configuration	Single input single output
Frequncy Bands	n1, n28, n41, **n78**
TDD-Pattern	5 ms periodicity, 5-7 DL, 2-7 UL slots
Bandwidths	**20**, 50, 90, 100 MHz
MCS Index	20
Uplink TX-Power	−20 dBm to 26 dBm

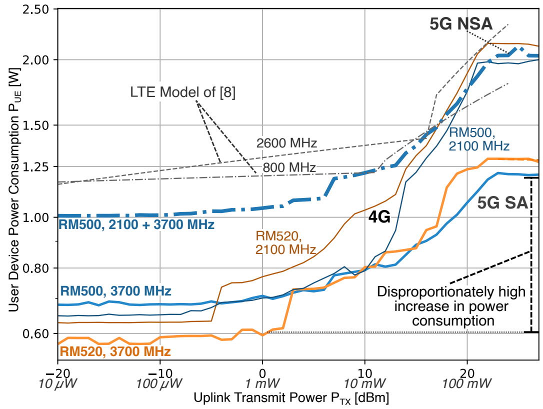


Fig. 4. 4G, 5G NSA and 5G SA power consumption at varying uplink transmit power P_{TX} and power consumption models of [8] for 4G.

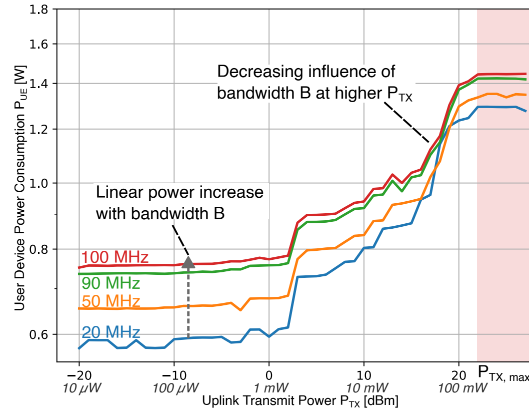


Fig. 5. Power consumption at different bandwidths B with a subcarrier spacing of 30 kHz over the uplink transmit power P_{TX}.

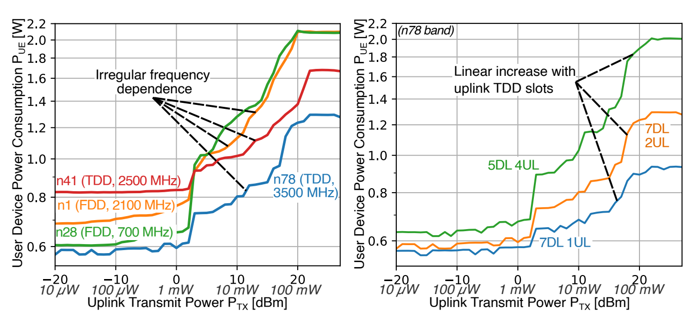
the number of allocated PRBs and the used MCSs, the cell frequency band and the Time Division Duplex (TDD) pattern. Each resulting power measurement is the average of two or more repetitions. Similar to the LTE measurements in [8] and NB-IoT and LTE-M measurements in [12], the slope of the UE power consumption is changing at distinct uplink transmit power levels, leading to a disproportionately steep rise in UE power consumption. However, as shown in Fig. 4, the power consumption of the 5G modems is even less in the lower transmit power region compared to the LTE smartphones used in [8]. This behavior might be due to the smartphone power consumption consisting of non-mobile network related hardware parts. The newer *RM520* modem draws even less power in the lower transmit power range under 3 dBm than the *RM500* modem. The difference in power consumption of 5G and 4G connections can be partly explained by device-dependent characteristics at the different utilized frequency bands (see also Fig. 6a). Additionally, Frequency Divison Duplex (FDD) is used for 4G in comparison to TDD for 5G. In the case of 5G NSA, two connections need to be maintained, leading to a higher power consumption in the lower transmit power region. We set up the data path to the 5G network part and thus only increased the 5G uplink transmit power while keeping the LTE transmit power at a low value similar to in real NSA networks. As a result, the rise in power consumption is similar to the 5G SA case. This behavior suggests that 5G NSA can only be energy efficient compared to LTE when large amounts of data are transmitted.

As in [8], the non-linear characteristic of the power consumption is approximated by a piece-wise linear function. However, as shown in Fig. 5, the power consumption is also approximately linearly increasing with the utilized bandwidth B of the cell. These device and technology-dependent parameters α_n, β_n and γ_n of the nth part of N linear functions are calculated for every device, as defined in Eqn. 2.

$$P_{\mathrm{UE}} = \begin{cases} P_{\max}, & P_{\mathrm{TX,\ max}} \leq P_{\mathrm{TX}} \\ \alpha_{\mathrm{N}} B + \beta_{\mathrm{N}} P_{\mathrm{TX}} + \delta_{\mathrm{N}}, & \gamma_{\mathrm{N\text{-}1}} \leq P_{\mathrm{TX}} < P_{\mathrm{TX,\ max}} \\ \dots & \\ \alpha_1 B + \beta_1 P_{\mathrm{TX}} + \delta_1, & P_{\mathrm{TX}} < \gamma_1 \end{cases} \quad (2)$$

The maximum possible data rate is linearly dependent on the bandwidth and only logarithmically on the SINR, leading to higher bandwidths reducing the energy consumption per bit in the uplink direction. As shown in Fig. 6b, the power consumption also rises linearly with increased TDD uplink slots. However, the achievable data rate is also linearly rising with more slots, compensating for the increased power consumption. Another influencing factor is the frequency band, as seen in Fig. 6a. For example, the FDD bands N28 and N1 draw more power compared to the n78 band. Further measurements have been conducted to rule out the influence of the selected MCS and the utilized number of PRBs.

As the UE power consumption mainly depends on the uplink transmit power, its value in the real world is of high interest. However, many commercial devices like *Android* smartphones do not provide this information at the application level. Thus, the uplink transmit power is predicted using machine learning. As there are two active links in current 5G NSA networks, in this work, a model is trained to predict the higher transmit power, which is the dominant factor. With the help of a dedicated modem on a suspension railroad, the transmit power could be directly measured during data transfers. For simplicity, a Random Forest (RF), as proposed in [13] for LTE networks, is utilized with a feature set of widely available passive signals. It is tuned by a random grid search approach optimizing the overall Root Mean Squared Error (RMSE) in combination with a ten-times cross-validation with a 20 % test set. This setup could reach a sufficient resulting test RMSE of 4 dB. For the uplink data rate, a similar machine-learning setup is used (see also [14]) trained on UDP uplink



(a) Frequency band (b) Time division duplex pattern

Fig. 6. Frequency band and TDD pattern dependent power consumption.

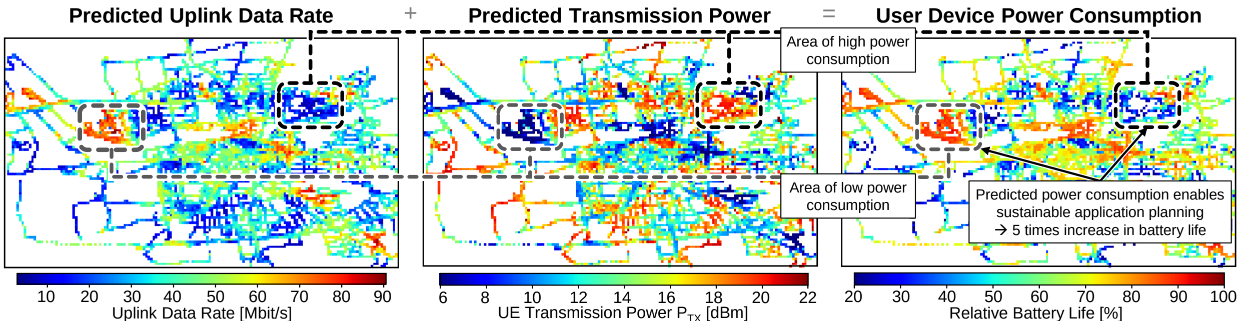


Fig. 7. User device power consumption based on uplink transmit power P_{TX} and data rate predictions for a 10 Mbit/s uplink use-case on a 50 m grid.

measurements with a file size of 10 MB. With the help of the achieved uplink data rate $D_{\text{UL}}(x, y)$ at a specific location (x, y), the best-case power-on-time portion p_{on} of the UE at a set target uplink data rate D_{target} can be estimated (see Eqn. 3).

$$p_{\text{on}} = D_{\text{target}}/D_{\text{UL}}(x, y) \tag{3}$$

It is assumed that the data path for the data transfer in current 5G NSA networks is via the 5G part of the mobile network, and no carrier aggregation is used. In this case, the power consumption of the data transfer is presumed to be the same as in 5G SA networks, allowing for a general estimate of the power consumption characteristics of these networks. The influence of the frequency band on the power consumption can be neglected, as all cells operated in the N78 frequency band. The conducted 5G SA power consumption laboratory measurements are used to derive the modem's power consumption P_{UE} based on the utilized transmit power P_{TX}, bandwidth B and the power-on-time portion p_{on}, as described in Eqn. 4. It is assumed that the UE is consuming a fixed power $P_{\text{idle}} = 0.2\,W$ in between the data transmit measured during airplane mode.

$$P_{\text{UE}} = (\alpha_{\text{n}} \cdot B + \beta_n \cdot P_{\text{TX}} + \delta_{\text{n}}) \cdot p_{\text{on}} + P_{\text{idle}} \cdot (1 - p_{\text{on}}) \tag{4}$$

With these assumptions, a power consumption map for a set application can be calculated. In a case study, the UE power consumption in the Dortmund city area shall be evaluated based on a high-quality video streaming scenario with an assumed data rate D_{target} of 10 Mbit/s. As shown in Fig. 7, based on our measurements and models, UE power consumption varies strongly in the Dortmund city area. While, on average, battery life in our scenario is above 60 % of the best case at most locations, the power consumption is over five times higher in some regions, resulting in a significantly reduced battery life. In these regions, both the data rate and the transmit power are predicted to be comparably disadvantageous for the UE (see Fig. 7). These high power consumption areas seem to occur more often outside the city center close to suburban areas and can severely decrease service quality of experience.

VI. Conclusion

In this paper, we transferred laboratory power consumption measurements into real-world user device power consumption estimations based on a massive data set of mobile network channel measurements in the Dortmund city area. With the help of an empirical context-aware power consumption model, the energy efficiency of UEs can be predicted. The model is coupled with machine learning to predict needed parameters. While the high number of influencing factors in the real world prevents an exact prediction of the power consumption of user devices, our proposed method reveals areas with a significantly higher power consumption. By avoiding these areas, the battery life of various applications can be increased drastically. It can vary up to five times due to the mobile network coverage depending on the location.

In the future, we plan to analyze the combination of Mobile Network Operators (MNOs) and technologies and extend our power consumption model to more system parameters, including MNO-dependent scheduling.

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