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On the Benefits of Demand-based Planning and Configuration of Private 5G Networks

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***Abstract*—High reliability and specific, application-driven requirements are the reason for the growing importance of private 5G networks or campus networks, which can be configured and deployed in a demand-driven manner. In this work, an experiment analyzing the need for demand-based configuration and planning of such private 5G networks is presented in form of a video, where a miniature racing track including a novel 5G-powered racing platform showcase two different 5G Standalone Time Division Duplex patterns for event-driven scenarios. Also, theoretical foundations are discussed together with the results of a simulative replica of the experiment, showing the benefits of demand-based configuration. These motivate the exploration of Machine Learning-based live planning and network parameterization which we present in our vision of future racing events, where private 5G networks can serve diverse participants, well-suited to their specific demands.**

I. Introduction

In addition to the much-discussed reference use case of stationary private 5G networks (or campus networks) for temporary use will also be of very great interest in the future whenever extremely demanding local requirements have to be met by the communications network. One example is major international events (Formula 1, America's Cup), where large amounts of data are required for event operations as well as for live audience engagement with low latencies and high reliability. In order to deploy these temporary networks quickly and flexibly, demand-driven and automated network planning and configurability are required [1].

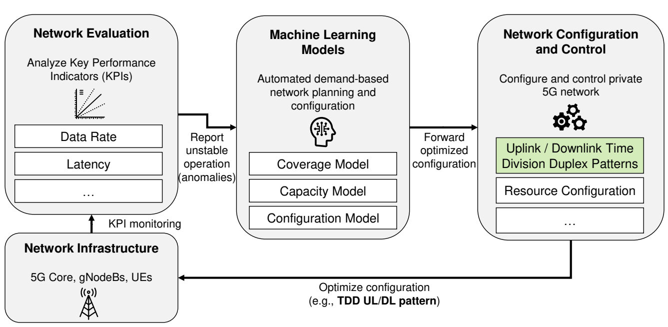


Fig. 1. Schematic depiction of the automated and demand-based network planning and configuration framework.

In Fig. 1, our concept of such a demand-based configuration and automated network planning framework is depicted. The *Machine Learning (ML) models* shown in the center calculate a network model based on the incorporated coverage, capacity, and configuration models based on given Quality of Service (QoS) targets. Note that the type of ML model used is part of future research and thus will be specified in later works. This initial network configuration is then forwarded to the *Network Configuration and Control* module, where the private 5G network infrastructure is configured based on this model. In the case of the experiment showcase presented here, the uplink and downlink Time Division Duplex (TDD) patterns are focused in particular. Furthermore, the *Network Evaluation* module analyzes Key Performance Indicators (KPIs) (e.g., data rate or latency) of the 5G network infrastructure (Core Network (CN), gNodeBs, User Equipments (UEs)) and reports possible unstable operation or anomalies to the *ML module*. This vision and the advantages of such a demand-driven configuration of the private 5G network is showcased in this work in form of a video, which will be described in the next sections.

There are related works which also analyze the benefits of dynamic configuration of 5G mobile networks. In [2] and [3] it is shown that the high performance of 5G networks when flexibly adapting the TDD pattern, instead of utilizing traditional static configurations. The authors in [4] present a Deep Reinforcement Learning-based algorithm to flexibly adapt the TDD pattern in order to maximize the throughput.

II. Demand-based Configuration and Planning of Private 5G Networks Experiment Showcase Video

The experiment is showcased in the form a video described in the following, which can be watched by scanning the QR-Code or by following the link given in Fig. 2.

Fig. 2. To watch the experiment showcase video, scan the QR-Code or use following link: http://tiny.cc/RacingWith5GSpeeds

The schematic description of the architecture of the experiment is provided in Fig 3. As depicted, two F1TENTH autonomous racing car platforms as well as an Unmanned Aerial Vehicle (UAV) (in a static, but cable-free setup) are utilized, which all carry a *Quectel RM500q* 5G Standalone (SA) modem.

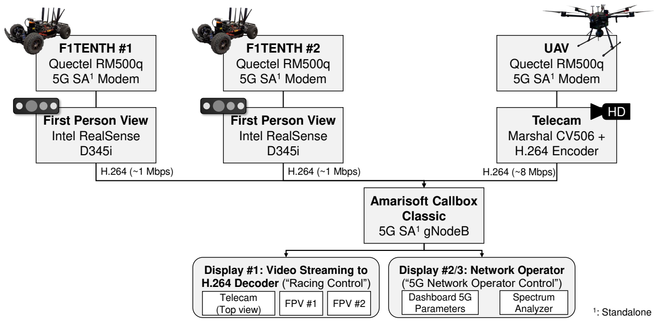


Fig. 3. Architecture of the experiment incorporating utilized hardware and communication infrastructure.

These serve as miniature versions of the network participants of a real-life racing scenario, where the first person views of the cars as well as full HD top-down camera (telecam) are transmitted over the 5G network in the uplink direction. The 5G network itself is provided by an *Amarisoft Callbox Classic* gNodeB at 3.75 GHz center frequency, 50 MHz bandwidth, and TDD transmission mode. Connected via the CN, two displays represent the *Racing Control* and *Network Operator* views of the event operation.

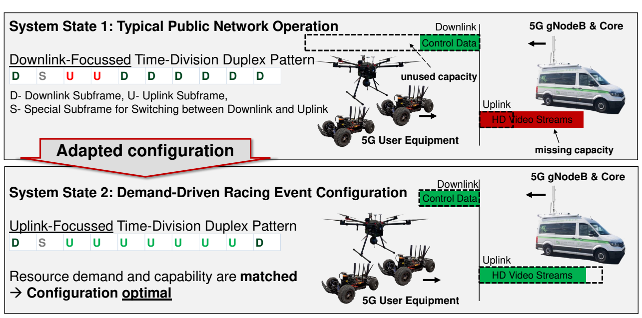


Fig. 4. The two different TDD patterns showcased in the experiment video represented by two system states.

As can be seen in the experiment video, two system states are showcased based on two TDD patterns, which are also depicted in Fig. 4. The first system state represents a typical public network operation, where the TDD pattern is more downlink-focused, while the second system state represents a demand-driven configuration for e.g. racing events, where the applications are more uplink focused, as described earlier. Furthermore, on the right hand side of the figure it can be seen that there is a high amount of unused capacity in the downlink and a high amount of missing capacity for system state 1. This anomaly is detected and adapted in system state 2 (cf. Fig. 1), where the utilized and needed capacity is matched by configuring the appropriate TDD pattern. The mismatch of system state 1 can be seen in the video by observing the Quality of Experience (QoE), which manifests itself as video stuttering and outages, where as in system state 2, all three video are stutter-free and thus, represent a high QoE.

The theoretical foundations for the adaptation and on why the adapted configuration leads to better QoE in the experiment showcase video are given in section III.

III. Theoretical Foundations and Results

As can be seen in Fig 4, two different TDD patterns are compared to show their real world impact patterns on underlying applications. The downlink-focused pattern consists of 7 downlink slots, 1 special slot and 2 uplink slots and represents a typical constellation utilized in end-consumer mobile communication networks, where UEs request much higher data amounts on the downlink than transmitting on the uplink. However, vertical industries or in this case event-driven communications represented by a racing event are much more reliant on uplink communications. In the course of the miniature racing event presented here, first-person views of the racecars as well as a top-down view of the racing event provided by a drone have to be transmitted via 5G uplink connection. This means that the typical downlink-focused pattern provided by most of available 5G infrastructure will not suffice. Utilizing an Software-Defined Radio (SDR)-based 5G gNodeB (*Amarisoft Callbox Classic*), the configuration is thus adapted to a more uplink-focused TDD pattern, which consists of only 2 downlink slots, 1 special slot, and 7 uplink slots. This means, that not only the throughput of the uplink is increased but also the time between the uplink slots is decreased, which is especially critical for the Real-Time Transport Protocol (RTP) utilized for the live video streams. In RTP, packets are dropped exceeding a defined delay where real-time transmission would be impaired. Thus, not only the higher throughput of the uplink-focused pattern leads to better QoE, but also the increased uplink transmission occasions and the decreased duration of the downlink slots.

TABLE I
Parameterization of the Simulative Validation Setup

Parameter	Value
OMNeT++ version	5.6.2
INET version	4.2
Simu5G version	1.1
Number of runs per configuration	25
Simulation time	60 s
Number of vehicular UEs	2
Transmission power	11 dBm
Slot configuration (UL-driven)	$n_{UL} = 7$, $n_{DL} = 2$
Slot configuration (DL-driven)	$n_{UL} = 2$, $n_{DL} = 7$
User Datagram Protocol (UDP) payload	1460 Byte
Traffic load (first person video stream)	1 Mbit/s
Traffic load (aerial drone video stream)	8 Mbit/s
Latency restriction	0.1 s

In order to quantify the subjective QoE measured in the experiment, we carry out a simulative replica of the real world setup. For this, we use Objective Modular Testbed in C++ (OMNeT++) in combination with the *Simu5G* framework [5] to deploy a gNodeB with a server behind to further decode and process received video streams. A static drone and two autonomously driven racecars are modeled as UEs and send out a constant bit rate UDP video stream with 8 Mbit/s and 1 Mbit/s respectively. As we consider the video streams to be real time data, we define a latency restriction $\tau_{\max} = 0.1$ s and, thus, limit the queue size at Radio Link Control (RLC) layer to

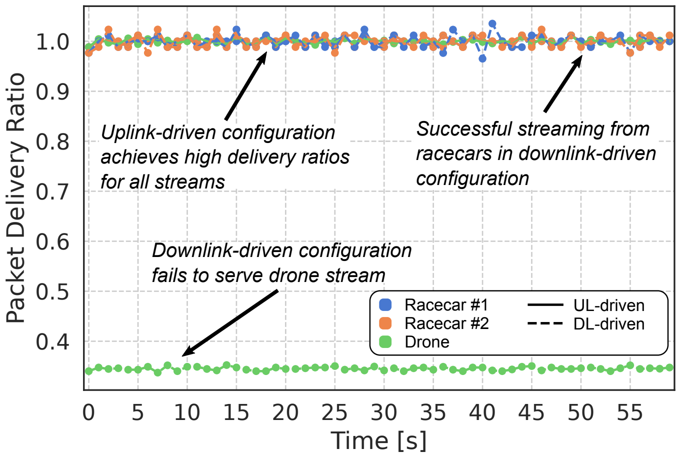
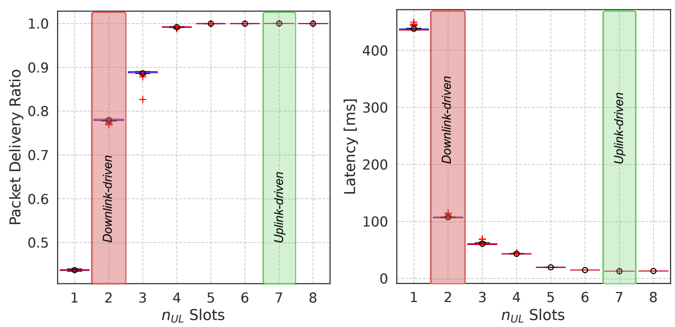


Fig. 5. Time course of the packet delivery ratio during one simulative experiment run.



(a) (b)

Fig. 6. Number of uplink slots n_{UL} with effect on the average packet delivery ratio (cf. (a)) and latency per run (cf. (b)) over 25 runs.

contain no more than the data created within $\tau_{\max}$. We monitor the end-to-end packet delivery ratio and latency as KPIs, whereas end-to-end means the span from UDP packet creation to the UDP packet reception. Thus, this KPI excludes video encoding and decoding and is considered as a representative of QoE impacts in the real world experiment. The default parameterization of the simulation setup is summarized in Tab. I

Fig. 5 shows the packet delivery ratio during an experimental run. For both slot configurations, a high KPI for the 1 Mbit/s first person view streams of the racecars can be observed. In contrast, the higher data rate stream of the drone shows significant losses in the downlink-driven setup compared to the uplink-driven system state, that confirm the QoE impressions in the video linked in Fig. 2. Missing packets cause video stuttering and fragments in the real world, because the video encoding utility is forced to interpolate individual frames as it lacks of sufficiently frequent incoming updates.

While this only considers two possible slot configurations, Fig. 6 evaluates the packet delivery ratio and end-to-end latency for different numbers of uplink slots n_{UL}. In the encountered configuration, there is a total of 10 symbols of which one is reserved as a special subframe. Consecutively, there are 9 remaining subframes to be assigned to uplink or downlink traffic each. It can be seen that there is a sweet

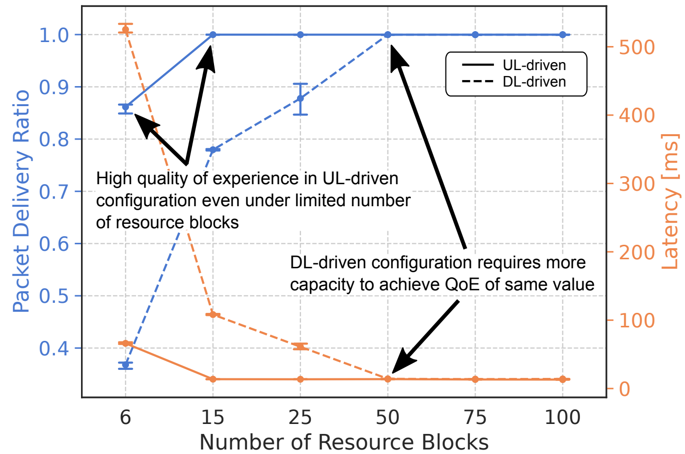


Fig. 7. Performances for uplink- and downlink-driven configurations in differently sized bandwidths.

spot, where the number of uplink slots in the TDD pattern is optimal for the applications given here. For our scenario, the packet delivery ratio is already optimal with 5 uplink slots, but the latency can be reduced by increasing it to the selected 7 uplink slots. These simulation results can be utilized in the configuration of future network deployments to further improve the predicted TDD patterns and reduce live reconfigurations.

Last, we simulated the KPIs for both types of configurations as shown in Fig. 7. For the considered numerology with 15 kHz sub-carrier spacing, the evaluated number of resource blocks $\{6, 15, 25, 50, 75, 100\}$ correspond to $\{1.4, 3, 5, 10, 15, 20\}$ MHz of bandwidth respectively. The results point out, that the uplink-driven and therefore demand-oriented configuration is capable to achieve high KPIs even under low available resources. The default downlink-driven state in turn, requires significantly more resources and, thus, wastes capacity. Especially in private 5th Generation of Mobile Communication Networks (5G) networks this shows the benefit of demand-based planning and configuration, as the resources of slices can be assigned more efficiently and, thus, enables a more economical usage of available resources, and possibly allows the deployment of further vertical applications.

IV. Outlook on Future Work

In this work, we have investigated a small-scale experiment for dynamic racing events and focused on the need for demand-oriented configuration and planning of private 5G networks. The application of Radio Access Network (RAN) configuration techniques to better fit the uplink/downlink characteristics of the data flow has shown significant improvements and motivates further research. However, we aim to follow an real-time auto-adjustable concept for private 5G networks. Our overall vision of network design for such events is shown in Fig. 8 with our current setup on the right, and our future goal being illustrated on the left. The four core elements are envisioned in the following:

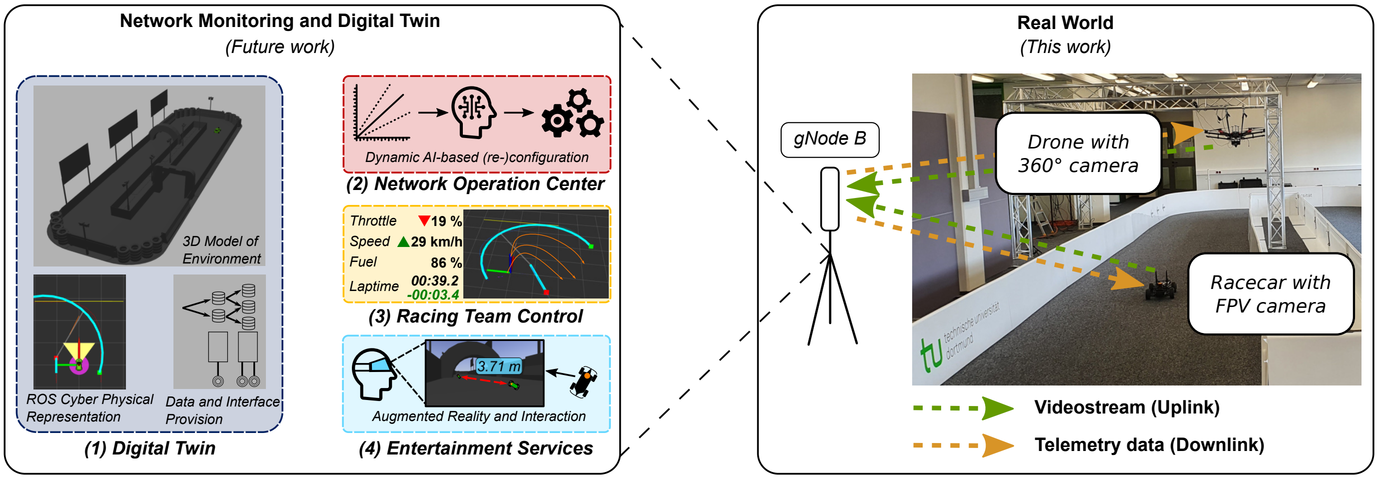


Fig. 8. Overall vision for the system design of a private 5G campus network to enable demand-based network operations, digital twinning, and event control. The illustrated core elements are: (1) digital twin, (2) network operation center, (3) racing team control, and (4) entertainment services.

(1) **Digital Twin:** The Digital Twin (DT) builds the most important component in our future system design, as it contains a full digital representation of the event in a 3D model, which allows a comprehensive data aggregation and the provision of interfaces to the other core elements. DTs are expected to be a key part of *6G*.

(2) **Network Operation Center:** The network operation center for instance can utilize the information from the DT to monitor the communication network. In future works, this is also the entry point to apply ML-based predictions to maintain and proactively reconfigure the network for demand-based needs. Previous works have already shown promising performance increases by applying predictions to network slicing [6]. Also intelligent routing can be enabled by leveraging trajectory knowledge through predictions [7]. The work in [8] presents an approach for context classification and dynamic auto-parameterization in extension of the latter. The authors in [9] describe QoS predictions for in-advance behavior to sustain the functionality of communication-based Vehicle-to-Everything (V2X) services under changing conditions.

(3) **Racing Team Control:** Further event participants to benefit from the DT are the racing teams themselves, that can leverage the information flow to monitor the racecar's performance, evaluate maneuvers in the digital representation before instructing the car to perform them, do predictive maintenance, and e.g. plan pit stop timings.

(4) **Entertainment Services:** The entertaining component of racing events is responsible for most of data traffic. Entertainment systems will experience new possibilities due to the interconnection with the DT. Augmented Reality (AR) is a well-known example to be expected for 5G and beyond technologies, where spectators will be able to follow the event and see context information and various perspectives in a digital representation of the event, which will happen in the DT.

Acknowledgment

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