# Data Transmission Plan Adaptation Complementing Strategic Time-Network Selection for Connected Vehicles

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**Abstract**

Connected vehicles can nowadays be equipped with multiple network interfaces to access the Internet via a number of networks. To achieve an efficient transmission within this environment, a strategic time-network selection for connected vehicles has been developed, which plans ahead delay-tolerant transmissions. Under perfect prediction (knowledge) of the environment, the proposed strategic time-network selection approach is shown to outperform significantly leading state-of-the-art approaches which are based either on time selection or network selection only. Under realistic environments, however, the efficiency of planning-based approaches may be severely compromised since network presence and available capacities change rapidly and in an unforeseen manner (because of changing conditions due to the uncertainty in car movement, data transmission needs and network characteristics). To address this problem, a mechanism is proposed in this paper that determines the deviation from the anticipated conditions and modifies the transmission plan accordingly. Simulation results show that the proposed adaptation mechanisms help maintain the benefits of a strategic time-network selection planning under changing conditions.

*Keywords:* network selection, transmission time selection, time-network selection, transmission plan adaptation, connected vehicles

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## 1. Introduction

Nowadays, mobile nodes typically integrate different wireless network interfaces. An example environment of wireless networks is shown in Figure 1, covering one mobile network (yellow) and three WiFi networks (blue, green, red) that are available for limited time spans during the trip. To improve connectivity performance, connected vehicles may use these networks in parallel to distribute their data traffic. Moreover, the connected vehicle use case provides an additional optimization potential, especially considering automated vehicles: Routes are usually known and, thus, movement can be predicted accurately. As a result, a vehicle can predict future network availability and characteristics using the so-called connectivity maps [1, 2]. A derived prediction of network availability over time is visualized in Figure 1 using colored bars. Furthermore, according to Sandvine [3], a major part of a mobile node's data traffic is delay-tolerant or heavy-tailed. Assuming networks and data traffic to be roughly known for a certain time horizon, we show in prior work [4] that a transmission planning can provide significant benefits. The transmission planning approach combines network selection [5] with a selection of the transmission time [6]. The approach plans ahead data transmission over multiple networks. In this paper, we present additional insights on the performance characteristics of this approach. However, the presented approach assumes perfect prediction of vehicle movement, network characteristics and data to transmit, as visualized in Figure 2 left. Such accurate prediction might not always be available. In the real world, further mechanisms have to cope with prediction errors. Accordingly, we present three contributions in this paper:

1. A strategic time-network selection approach that maximizes transmission efficiency using heterogeneous wireless networks due to transmission planning (Figure 2 blue arrow).
2. An investigation of the effects of erroneous prediction on the performance of transmission plan execution (Figure 2 red arrow)
3. A transmission plan adaptation that can mitigate a negative impact of erroneous prediction (Figure 2 green arrow)

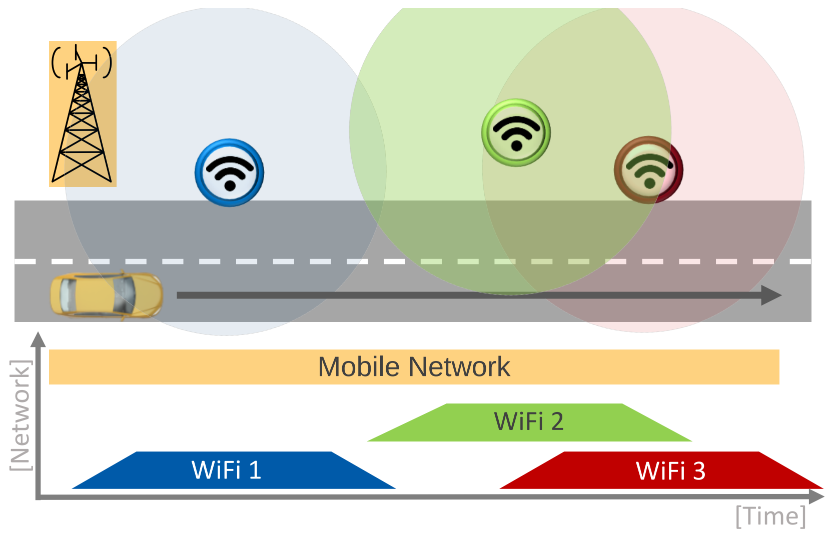


Figure 1: Connected vehicle using heterogeneous wireless networks: example scenario

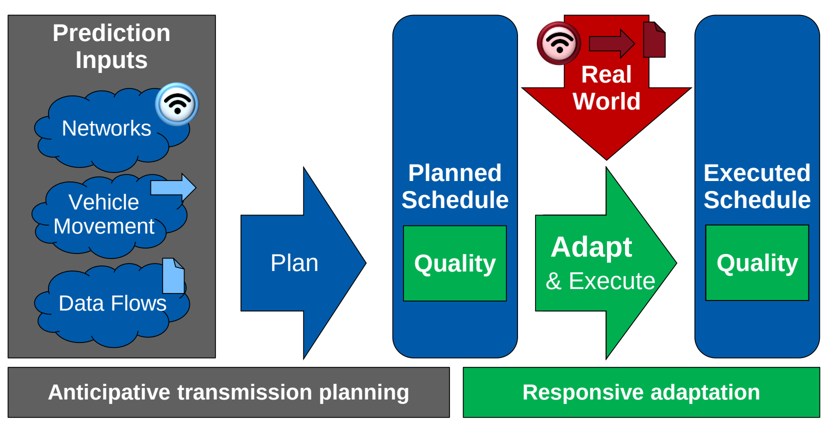


Figure 2: System overview: prediction-based transmission planning complemented by adaptation for plan execution

In Section 2, we briefly outline our previous work on an anticipative data transmission planning assuming static conditions and perfect knowledge of the environment and compare it to an Opportunistic Network Selection (ONS) (no planning or prediction). We show its performance characteristics in different scenarios and compare it also to other state-of-the-art-based approaches. Furthermore, we introduce our prediction error models and show that the performance of the strategic time-network selection approach degrades severely in the presence of prediction errors, due to its inability to react to changing conditions. In contrast, the opportunistic approach – although underperforming with respect to the transmission plan approach under static conditions and perfect knowledge – appears to deliver a constant performance in the presence of prediction errors. This provides the motivation for our proposed transmission plan adaptation mechanism, presented in Section 3, which complements the transmission planning. The benefit of each planned transmission is re-evaluated and the planned transmission is modified by invoking a constrained ONS taking into account the type and magnitude of condition changes (i.e., car movement, data flows or network characteristics); mechanisms detecting relevant condition changes are also introduced. In Section 4, we discuss the performance of our novel adaptation approach under various changing conditions, followed by a related work discussion in Section 5. It turns out that our responsive adaptation approach can largely sustain the gain foreseen from anticipative transmission planning with strategic time-network selection under small to moderate changes in the environment.

## 2. Data Transmission Planning

The predictable movement of multi-homed mobile clients enables a transmission planning over networks and time. In our prior work [4], we demonstrate significant benefits of such a planning in comparison to state-of-the-art approaches. In this section, we summarize the approach, the evaluation metrics and results of this work and extend it with new insights. This constitutes the base for the adaptation approach proposed and evaluated in this paper.

### 2.1. Evaluation Metrics and Model of Forces

To assess the efficiency of our strategic time-network selection approaches, we developed a performance rating function, that captures application QoS requirement satisfaction and monetary cost. We bisect the performance rating function into two components that are in effect in a mutually exclusive manner depending on whether data is allocated or not. We call the first component the attracting forces $c_{attr}$. It captures cost associated with data that is not allocated to a network, punishing the violation of a minimum throughput requirement and the amount on non-allocated data. The second component, referring to as the repelling forces $c_{rep}$, captures cost associated with data that is allocated to a network, punishing the violation of the QoS requirements of the data flows or monetary transmission cost. It covers components from network selection, like latency, jitter and also components from transmission time selection approaches, including deadline and the preferred start time of data transmissions, as visualized in Figure 3.

Networks attract data for allocation in general through $c_{attr}$, creating attracting forces for each data flow according to its priority. In addition, the repelling forces push data away from networks and time slots that cannot satisfy the data flow's QoS requirements. The rating function in Equation (1) adds the two mutually exclusive components for a given transmission plan $p$. Note that $p^*$ is an alias for $p$, indicating that the given model component punishes the absence of a desired transmission in a plan.

$$c(p) = c_{attr}(p^*) + c_{rep}(p) \tag{1}$$

Minimizing the cost function results in a data allocation to the best matching networks at matching points in time over the complete planning time horizon. For the detailed model of the cost function, refer to [4]. It is summarized in Figure 3.

As the absolute value of the cost in Equation (1) strongly depends on the scenario, a Normalized Rating Score (NRS) is introduced to allow for a meaningful comparison of multiple scenarios. *NRS describes a transmission plan's achieved share of the absolute*

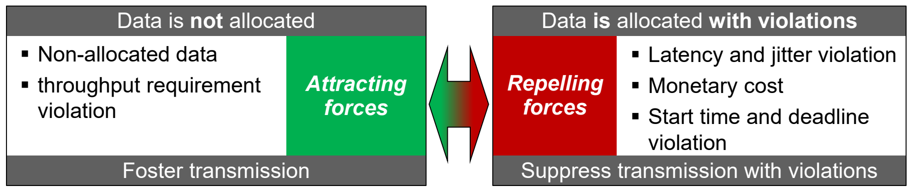


Figure 3: Transmission rating using a model of forces

*optimization potential of the given scenario.* A value of 0.8 means that a transmission plan uses 80% of the scenario's optimization potential. To define the optimization potential, we employ an upper and a lower cost bound. As a lower cost bound, we use the cost of an optimal transmission plan. As an upper cost bound, we use the average cost of random transmission plans. We assume this as a reasonable upper cost bound for rating because no transmission plan, which was created with intent, should perform worse than random. Higher values are still feasible.

### 2.2. *Transmission Planners*

Transmission planners determine data allocation to networks and over time. We analyze three transmission planners from [4] in this paper and an additional one for transmission time selection. All of them use the same ratings for network selection and data flow prioritization to create comparability of their results. However, they differ in the way they handle the time dimension.

The first is a **Network Selection (NS)** is derived from state-of-the-art approaches and allocates data to the *currently* available networks ignoring the time dimension. It prioritizes data flows and decides for each one, which *currently* available networks are best suited for its transmission. Finally, it allocates data according to these priorities. Note that it transmits in a best effort fashion, utilizing the selected networks at their maximum transmission rate.

As a second approach, we present an **Opportunistic Network Selection (ONS)**. It extends Network Selection by considering an opportunistic component, which decides *whether to transmit data* (as the NS would dictate) *or not*. This decision is based on an estimated benefit, defined as the difference between the estimated repelling $c_{\widetilde{rep}}(p_{f,t,n})$

(in case data is transmitted) and the estimated attracting $c_{\widetilde{attr}}(p^*_{f,t,n})$ (in case data is not transmitted) forces. Whenever the benefit exceeds some threshold $c_{lim}$, the approach allocates data to the network. This is shown in Equation (2), showing the cost difference for a specific data allocation of data flow $f$ at time slot $t$ to network $n$. Rejecting non-beneficial transmission at the current point in time amounts to waiting for a better opportunity to transmit.

$$c_{\widetilde{attr}}(p^*_{f,t,n}) - c_{\widetilde{rep}}(p_{f,t,n}) > c_{lim} \tag{2}$$

In addition to these two network selection approaches, we present **Delayed WiFi Offloading (DWO)** as a leading approach from the transmission time selection domain. It ignores the flow-network matching and follows a basic WiFi-preferred strategy, not considering most QoS requirements of data flows. The approach seeks to transmit as much data as possible via WiFi. Therefore, it plans ahead data transmissions of delay-tolerant data flows, assigning their transmission to a point in time when WiFi networks are assumed to be available. Hence, it requires a prediction of network availability and data rates. The transmission delay is determined by considering a maximum *planning time horizon* complying with the prediction time period and the data flow's deadline. These three approaches are generalized from leading state-of-the-art approaches and serve for performance comparison to our own approach, presented in the following.

As a fourth approach, we present our **Joint Transmission Planning (JTP)**, as introduced in [4]. Instead of considering the currently available networks only, JTP selects the *best transmission opportunities within the complete planning time horizon*. Thus, it combines the planning concept from transmission time selection with an elaborated flow-network matching from network selection. It plans data allocation ahead for a time, in which the transmission is expected to be most beneficial. In addition, it uses the opportunistic component from ONS to be able to move delay-tolerant transmissions beyond the planning time horizon in case of insufficient transmission opportunities. Hence, it represents a strategic time-network selection, which handles both dimensions, time and networks, explicitly. However, the approach requires a prediction of network availability and characteristics, of client movement and of the data to transmit.

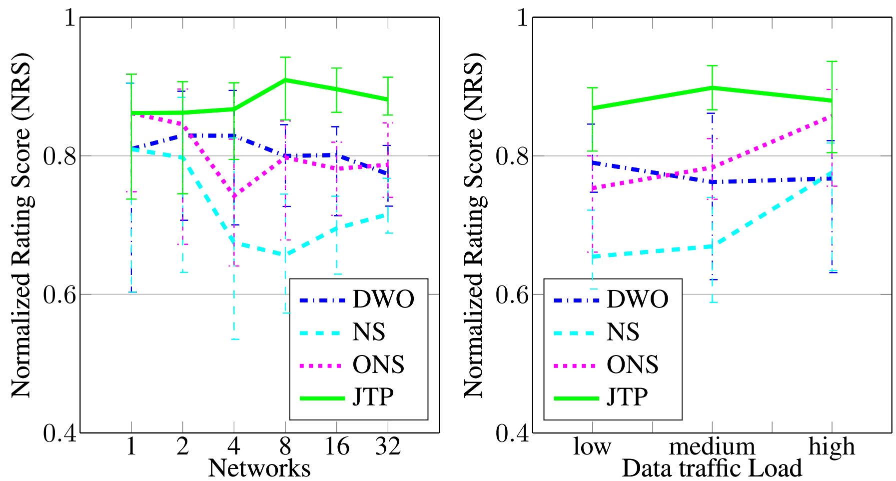


Figure 4: Normalized Rating Score (NRS) of the transmission planners for different number of networks in the planning time horizon (left) and different amounts of data traffic of the vehicle (right)

Table 1: T-test results over number of networks for $H_0$ : $\overline{JTP} = \overline{ONS}$ and $\overline{JTP} = \overline{DWO}$

| Networks | 1 | 2 | 4 | 8 | 16 | 32 |
|---|---|---|---|---|---|---|
| $p_{\overline{JTP}=\overline{ONS}}$ | **0.81** | **0.47** | $3.7 \cdot 10^{-6}$ | $1.8 \cdot 10^{-7}$ | $2.8 \cdot 10^{-10}$ | $1.9 \cdot 10^{-7}$ |
| $p_{\overline{JTP}=\overline{DWO}}$ | **0.74** | **0.43** | **0.14** | $3.2 \cdot 10^{-7}$ | $2.6 \cdot 10^{-8}$ | $3.5 \cdot 10^{-9}$ |

Table 2: T-test results over data traffic load for $H_0$ : $\overline{JTP} = \overline{ONS}$ and $\overline{JTP} = \overline{DWO}$

| Data traffic load | low | medium | high |
|---|---|---|---|
| $p_{\overline{JTP}=\overline{ONS}}$ | $1.0 \cdot 10^{-6}$ | $6.7 \cdot 10^{-11}$ | **0.096** |
| $p_{\overline{JTP}=\overline{DWO}}$ | $0.006$ | $1.2 \cdot 10^{-10}$ | $4.9 \cdot 10^{-7}$ |

We simulate the different approaches with default parameters of a planning time horizon length of 100 time slots (1 second each), 8 networks (2 mobile, 6 WiFi) in the planning time horizon, a medium amount of data traffic that utilizes about 70% of the available network resources, consisting of 8 individual data flows. Characteristics follow a default mobile data traffic distribution [3]. Figure 4 presents the Normalized Rating Score results of the transmission planners for different number of networks (1 to 32) in the planning time horizon and for different amounts of data traffic (low, medium, high) of the vehicle. More details about the simulation setup are available with the source code for reproducibility and possible extension of this work, see acknowledgments.

Under varying number of networks, the Network Selection (NS, as a dashed light blue line) and Opportunistic Network Selection (ONS, as a dotted magenta line) show similar trends. They perform well with a median NRS of 79-86% when there is just a single or two networks available within the planning time horizon. However, in these scenarios, there is not much choice which makes selection almost obsolete. Accordingly, all approaches perform well. As soon, as there are several networks to select from, i.e. there exists a certain optimization potential in the scenario, their performance drops significantly to median 67%, respectively 74%. For a large number of networks, their relative performance starts to recover. The reason for that is a saturation of "good" networks in the scenario, meaning that for a large number of networks within the planning time horizon, there is a good network available at nearly any point in time, rendering time selection obsolete. The two effects lead to an inverse performance characteristic for the transmission time selection approach Delayed WiFi Offloading (DWO, dash-dotted dark blue).

These results show that our strategic time-network selection approach Joint Transmission Planning (JTP, green solid) yields always high performance of 87-91% of the optimization potential. JTP outperforms the state-of-the-art approaches in average by 15.47% (NS), 7.71% (ONS) and 7.26% (DWO). Table 1 presents the t-test results of the analyzed approaches. The test calculates the probability $p$ that two data sets belong to the same distribution. For a probability of $p < 0.05$, we denote a difference between two distributions as significant. Insignificant differences with $p \geq 0.05$ are printed bold. The results dignify that that the observed performance gains of our approach JTP are significant as soon as the scenario covers a couple of networks, i.e. there exists a certain optimization potential in the scenario.

Figure 4 right shows the evaluation results for scenarios in which the vehicle transmits a different amount of data. With a rising amount of data traffic NS and ONS perform better. Again, this is linked to the optimization potential of the scenario. When a lot of data has to be transmitted, nearly every transmission opportunity has to be used. Hence, there is little flexibility in leaving out unfavorable transmission opportunities which renders transmission time selection less important. Accordingly, network selection approaches perform relatively better under high data load. In contrast, DWO which lacks an appropriate network selection shows an inverse characteristic. It performs better in scenarios with low data traffic providing a high flexibility for leaving out transmission opportunities.

Our strategic time-network selection approach JTP, which combines the advantages of the three approaches generalized from state-of-the-art, shows superior performance for all scenario variations, reaching again 87-91% of the optimization potential. JTP outperforms the state-of-the-art approaches in average by 18.23% (NS), 8.41% (ONS) and 10.90% (DWO). As shown from the t-test results in Table 2, if there is a certain optimization potential, these performance gains are significant.

Conclusively, the results demonstrate the huge benefits of a strategic time-network selection. It achieves a significantly higher transmission efficiency of up to 18% when using heterogeneous wireless networks.

The results for the strategic time-network selection approach JTP in Figure 4 are derived assuming perfect knowledge of the environment, i.e. network resources and demand characteristics. As this can hardly be the case in real environments, predictions about the state of the environment in the future will not be perfect, as indicated in Figure 2 with the red arrow. In the remainder of this paper, we first introduce prediction error models and analyze the impact of these errors on the performance of the four planners. Second, we propose a transmission plan adaptation approach that takes into account prediction errors, which is the main contribution of this paper.

## 3. Adaptation of Transmission Plans

Transmission plans are applicable whenever prediction is correct. Nevertheless, what does happen if the prediction used for transmission plan creation is erroneous? In this section, we analyze prediction error types of the connected vehicle use case and design a novel adaptation approach with the goal of robustness against this kind of uncertainty.

### *3.1. Prediction Errors*

In a connected vehicle environment, as exemplified in Figure 1, transmission plans can be derived based on some predictions on the vehicle movement, the encountered network characteristics and the data to be transmitted. As such predictions may be incorrect, it is important that resulting prediction errors are calculated and some adjustments in the transmission plan are made. The Symmetrical Mean Absolute Percentage Error (SMAPE) [7] is employed to measure those prediction errors. The movement prediction error mainly affects the availability of networks. For example, a vehicle, which moves faster than expected, may reach a small range network earlier and may spend less time in its covered area. We measure the error in the number of time slot drifts over the planning horizon. The network characteristics prediction error affects the throughput, latency and jitter of the networks over time. Finally, the data flow prediction error arises from canceling or pausing running data transmissions or from unexpected new data transmissions. Next, we present our adaptation approach handling these three types of errors.

### *3.2. Adaptation Approach*

The idea of our adaptation approach is to use a constrained Opportunistic Network Selection (ONS) whose decision threshold $c_{lim}$ is determined according to environmental changes so that the data transmission plan that is actually implemented is still beneficial. First, we design a transmission plan execution algorithm, which constraints ONS to implement the initial transmission plan, when no environmental changes occur. Second, to allow ONS to adapt the plan as a reaction to environmental changes, we present three adaptation mechanisms that dynamically relax the constraints and modify parameters of the first algorithm.

*Execution Algorithm (Exec):* To follow an initial transmission plan, this algorithm suppresses each data transmission, which does not comply with the plan. Therefore, the mechanism increases the benefit threshold $c_{lim}$ of the base approach ONS to the flow's maximum benefit value $c_{max}(f,t)$, defined as the supremum of its attracting force according to Equation (3). When, in contrast, data is allocated in the initial plan, it sets the threshold to the flow's minimum benefit value $c_{min}(f,t)$, defined as the infimum of its repelling forces, which is based on the highest requirement violations from the currently available networks $N_0$ according to Equation (4). To decide which of the two threshold values to use, the approach compares the amount of released data $p^{rel}(f,t_0)$ from Equation (5) to the actually allocated data $s^{alloc}(f,t_0)$ of data flow $f$ from Equation (6) at the current time slot $t_0$ according to Equation (7). While the released data $p^{rel}(f,t_0,n)$ does not change over time within the considered time slot, the value of the allocated data $s^{alloc}$ is refreshed continuously, stopping the allocation as soon as the amount of the data planned for the current time slot is transmitted. This completes the ONS-based transmission plan execution algorithm. In the following, we enhance this algorithm with mechanisms for transmission plan adaptation as a reaction to recognized prediction errors of the networks, the node movement and the data flows.

$$c_{max}(f,t) = \sup_{t \in T} c_{attr}(p^*_{f,t,n}) \tag{3}$$

$$c_{min}(f,t) = \inf_{n \in N_0} c_{rep}(p_{f,t,n}) \tag{4}$$

$$p^{rel}(f,t_0,n) = p_{f,t_0,n} \tag{5}$$

$$s^{alloc}(f,t_0,n) = s_{f,t_0,n} \tag{6}$$

$$c_{lim} = \begin{cases} c_{min}(f), & s^{alloc}(f, t_0, n) < p^{rel}(f, t_0, n) \\ c_{max}(f), & else \end{cases} \tag{7}$$

### *3.2.1. Extended Data Release Mechanism*

Our first adaptation mechanism addresses **changes in the network characteristics**. This corresponds, firstly, to changed transmission characteristics like latency and jitter and, secondly a differing throughput. Changes in network characteristics may affect the flow-network matching and preference. Strong performance degradation of networks might lead to the case in which transmission is not beneficial at all. To let the constrained ONS decide whether to transmit or not, we set the minimum threshold $c_{min}$ to the ONS's default value 0 according to Equation (8). Other values would be feasible as well. Higher values restrict transmission to opportunities with a higher benefit. This may lead to a better flow-network matching but may also suppress some transmissions completely. The value 0 provides a good trade-off. It restricts each data allocation to the cases for which ONS still considers a sufficient benefit. In addition, we relax constraints to employ ONS for re-evaluation of the flow-network matching and a re-selection using the actual network characteristics. Therefore, we stop distinguishing between networks for releasing data. To this end, we constrain all networks in the current time slot equally by considering the sum of allocated data over all networks, as shown in Equations (9) and (10).

To address unbiased fluctuations of the network throughput, we relax the execution algorithm's limit for the amount of released data. Instead of focusing on the amount of data planned for transmission for each time slot separately, we redefine the released data $p^{rel}(f)$ according to Equation (9) to cover all data allocated in the initial plan until the current point in time $t_0$ plus the flow's data, which has not been allocated in the initial plan at all $p^*_f$. Thus, data may also be allocated at good transmission opportunities after the planned transmission time. This helps the approach to cope with unbiased fluctuating network throughput and allows the constrained ONS to fill unexpected additional network resources opportunistically with initially non-allocated

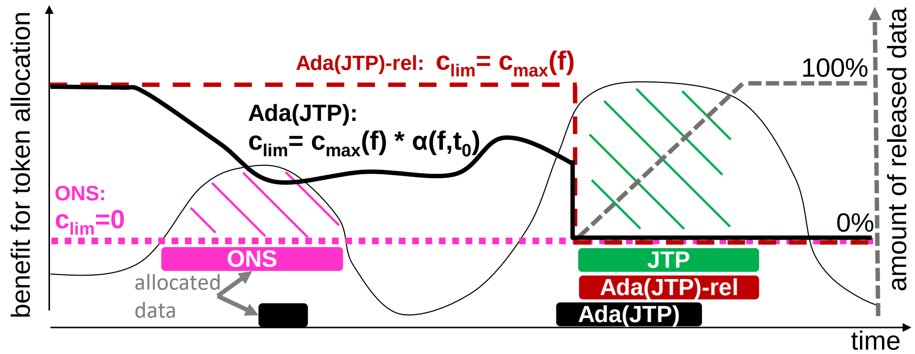


Figure 5: Schematic of basic concept

data $p_f^*$.

$$c_{min}(f,t) = 0 \tag{8}$$

$$p^{rel}(f,t_0,n) = p_f^* + \sum_{t=0}^{t_0} \sum_{n \in N} p_{f,t,n} \tag{9}$$

$$s^{alloc}(f,t_0,n) = \sum_{t=0}^{t_0} \sum_{n \in N} s_{f,t,n} \tag{10}$$

Figure 5 visualizes the characteristic behavior. Firstly, it shows the benefit over time for allocating data as a black thin curve. Allocating data with higher benefit leads to a lower cost function value, representing a better transmission. In addition, the figure contains lines for the cost benefit threshold $c_{lim}$ of ONS (pink). ONS sets $c_{lim} = 0$ by default, thus allocating data at the earliest point in time offering a transmission benefit. In the example, ONS transmits during the first benefit 'hill', during the pink marked time span. We consider the transmission to be finished after that time span in the example. In contrast, the Joint Transmission Planning approach (JTP, green) allocates data at the transmission opportunity with the highest benefit; in the example the second 'hill'.

As indicated in Figure 5 by the gray dashed line at the right, the extended data release mechanism (red) releases data for allocation according to the plan of JTP. It suppresses data transmission until the plan of JTP holds allocations. Thus, a data allocation in the plan allows the mechanism to transmit data opportunistically. In case of no prediction errors, this results in setting the cost benefit threshold $c_{lim}$ according to the red line, which lets this adaptation mechanism *Ada(JTP)-rel* stay close to the initial plan.

### 3.2.2. Location reference mechanism

To cope with **movement prediction errors**, we present our corresponding adaptation mechanism, which refers to the initial plan by vehicle location instead of time. When a vehicle moves e.g. faster than predicted, it reaches and leaves short range networks earlier than expected. Compared to the prediction, location dependent network characteristics move to another point in time. As a result, network availability is modified from the initial time-line, impairing on the network selection of the transmission plan. Furthermore, for delay-tolerant data transfers, it is more important to sustain the network-matching then to sustain the selected transmission time. To address this issue, we employ the following mechanism: *For delay-tolerant data flows, consider the spatial dimension in the transmission plan, i.e. the vehicle's location, and ignore the temporal one.* Referring to the spatial dimension is equivalent to a temporal offset $\epsilon_{move}(t_0)$ of the transmission plan. The location reference mechanism shifts data transmission in time by this temporal offset to preserve the initial network selection. However, for non-delay-tolerant data flows, e.g. interactive ones, this temporal transmission offset may lead to a temporal requirement violation. Hence, we limit the temporal offset $\epsilon_{move}(t_0)$ to the maximum delay-tolerance of the data flow, which our model from prior work [4] encodes in a throughput requirement window parameter $\Delta\widehat{t}_f^{min}$, c.f. Equation (11). Accordingly, we employ the time-limited spatial reference $t^{loc}(f, t_0)$ according to Equation (12) to refer to the initial plan. This limited spatial reference preserves the initial network selection of the transmission plan for delay-tolerant data flows but accounts temporal requirements for non-delay-tolerant flows.

$$t_f^{offset} = \min(\Delta\widehat{t}_f^{min}, \|\epsilon_{move}(t_0)\|) \tag{11}$$

$$t^{loc}(f, t_0) = \begin{cases} t_0 + t_f^{offset}, & \epsilon_{move}(t_0) > 0 \\ t_0 - t_f^{offset}, & else \end{cases} \tag{12}$$

Referring to the corresponding vehicle location in the transmission plan to release data for allocation in the presented manner causes one problem: whenever the car stops, no additional data is released. There is no progress in the vehicle's location and, thus, the transmission pauses. This effect impairs transmission similarly when the car moves slower than expected. To address this issue, our mechanism modifies the condition for the $c_{lim}$ threshold selection of Equation (7) to that from Equation (13). *Whenever data is allocated within the initial plan in the reference time slot, release data for transmission.* Hence, this mechanism together with the extension in triggering conditions handles movement prediction errors up to a certain degree.

$$\begin{aligned} s^{alloc}(f, t_0, n) &< p^{rel}(f, t^{loc}(f, t_0), n) \\ \text{or } \left( \sum_{n \in N} p_{f, t^{loc}(f, t_0), n} \right) &> 0 \end{aligned} \tag{13}$$

### *3.2.3. Flow Prediction Error Handling*

Finally, our third mechanism treats **flow prediction errors**. Flow prediction errors refer to additional data to be transmitted, time shifts in data transmission and canceled data transmission. For new data, there exists no reference in the existing transmission plan. Hence, we let the mechanism release new data completely for opportunistic transmission, handling it equivalently to the non-allocated data $p_f^*$. This way, the opportunistic algorithm automatically prioritizes active data flows correctly, integrating the new ones into the ongoing transmission. However, prediction errors concerning planned transmissions have to be treated explicitly because they interfere with other planned transmissions. This covers especially planned non-delay-tolerant data flows, whose transmission time differs from the predicted one. Hence, we consider the SMAPE flow prediction error $\epsilon_{flow}(f, t)$ over the time span of the past throughput window $\Delta \widehat{t}_f^{min}$ of the flow. However, for delay-tolerant flows, a pure opportunistic transmission might lead to a worse network selection. Hence, instead of setting $c_{lim}$

to 0, we reduce $c_{max}$ with rising error according to Equation (14) and (15). Thus, *when flow prediction errors occur, our approach does not suppress data allocation but restrict it to opportunities in which an error-dependent benefit threshold is reached.* We illustrate an example threshold adaptation $\alpha(f, t_0)$ from Equation (14) in Figure 5 with a thick black line. In the example, this results in a partially earlier transmission of Ada(JTP). The final transmission plan adaptation mechanism is given in Equation (16).

$$\alpha(f, t_0) = 1 - \sum_{t=t_0-\Delta\hat{t}_f^{min}}^{t_0} \frac{\epsilon_{flow}(f, t)}{\Delta\hat{t}_f^{min}} \tag{14}$$

$$c_{max}(f, t_0) = \sup_{t \in T} c_{attr}(p^*_{f,t,n}) \cdot \alpha(f, t_0) \tag{15}$$

**Final adaptation algorithm threshold:**

$$c_{lim} = \begin{cases} 0, & \begin{array}{c} s^{alloc}(f, t_0, n) < p^{rel}(f, t^{loc}(f, t_0), n) \\ \text{or} \quad \left( \sum_{n \in N} p_{f, t^{loc}(f, t_0), n} \right) > 0 \end{array} \\ \sup_{t \in T} c_{attr}(p^*_{f,t,n}) \cdot \alpha(f, t_0), & else \end{cases} \tag{16}$$

Conclusively, our transmission plan adaptation approach combines the advantages of Opportunistic Network Selection and Joint Transmission Planning. Thus, it allows for opportunistic transmission when high prediction errors render parts of an initial plan infeasible but can exploit the superior transmission patterns in terms of time and network selection from anticipative transmission planning. We evaluate the effects of the execution (Exec) and the three adaptation mechanisms (Ada) within the next section.

## 4. Evaluation

To analyze the performance of the transmission plan adaptation mechanism (Ada), we assess its performance under controlled variation of the prediction errors with the above presented Normalized Rating Score (NRS) and compare it to that of the Opportunistic Network Selection (ONS) and the pure plan Execution (Exec). As additional performance reference, we show the results of Joint Transmission Planning (JTP) with perfect prediction. JTP uses this perfect prediction for all modified scenarios, independent from the defined error on the x-axis. It defines an upper bound for reference. We apply the different approaches to scenarios with 100 time slots, covering 2 cellular networks and 6 WiFi networks, which are available within the scenario's planning time horizon. The number of data flows is initially 8 and varies due to flow prediction errors. We apply the different approaches to 50 randomized scenarios per run. For execution of each instance, we use a single core of a server machine with Intel Xeon E5-2643 v3 @ 3.4GHz and 512 GB RAM. To show the typical performance and its distribution, we give the $Q_{25\%}$, $Q_{50\%}$ (median) and $Q_{75\%}$ quantiles. We vary the prediction errors (SMAPE) separately for movement, network characteristics, data traffic and finally for a combined one between 0.0 and 0.5. We let the adaptation approach follow the plan of JTP and abbreviate the different mechanisms with (1) Ada(JTP)-rel: ONS with the data release mechanism (2) Ada(JTP)-rel-loc: with additional location reference mechanism and (3) Ada(JTP): the final approach covering all three mechanisms.

The results are presented in Figure 6, showing the graphs for each of the error types and the combined case. First of all, we notice that in presence of environmental changes the pure execution of the plan Exec(JTP) (dashed light blue) suffers substantially from robustness. It sinks far below the performance of ONS even for small prediction errors. This performance drop demonstrates that a pure execution is not efficient in reality and an adaptation is required.

In contrast, the performance of our adaptation approach (black solid) stays approximately between those of JTP and ONS, starting at the JTP's and converging towards the ONS's performance for rising errors. Increasing the network prediction error (a) shows that our basic data release mechanism Ada(JTP)-rel (dashed red) is able to handle this error type well. Even at an error of 0.5, the adaptation sustains a gain from anticipative transmission planning of about 4.5% NRS over ONS which corresponds to 36.23% of the performance margin between JTP and ONS. However, the basic data release Ada(JTP)-rel (dashed red) algorithm's performance decreases fast with rising movement prediction error (b). Adding the spatial reference algorithm Ada(JTP)-rel-loc (dotted blue), which we designed to cope with this error type, resolves this is-

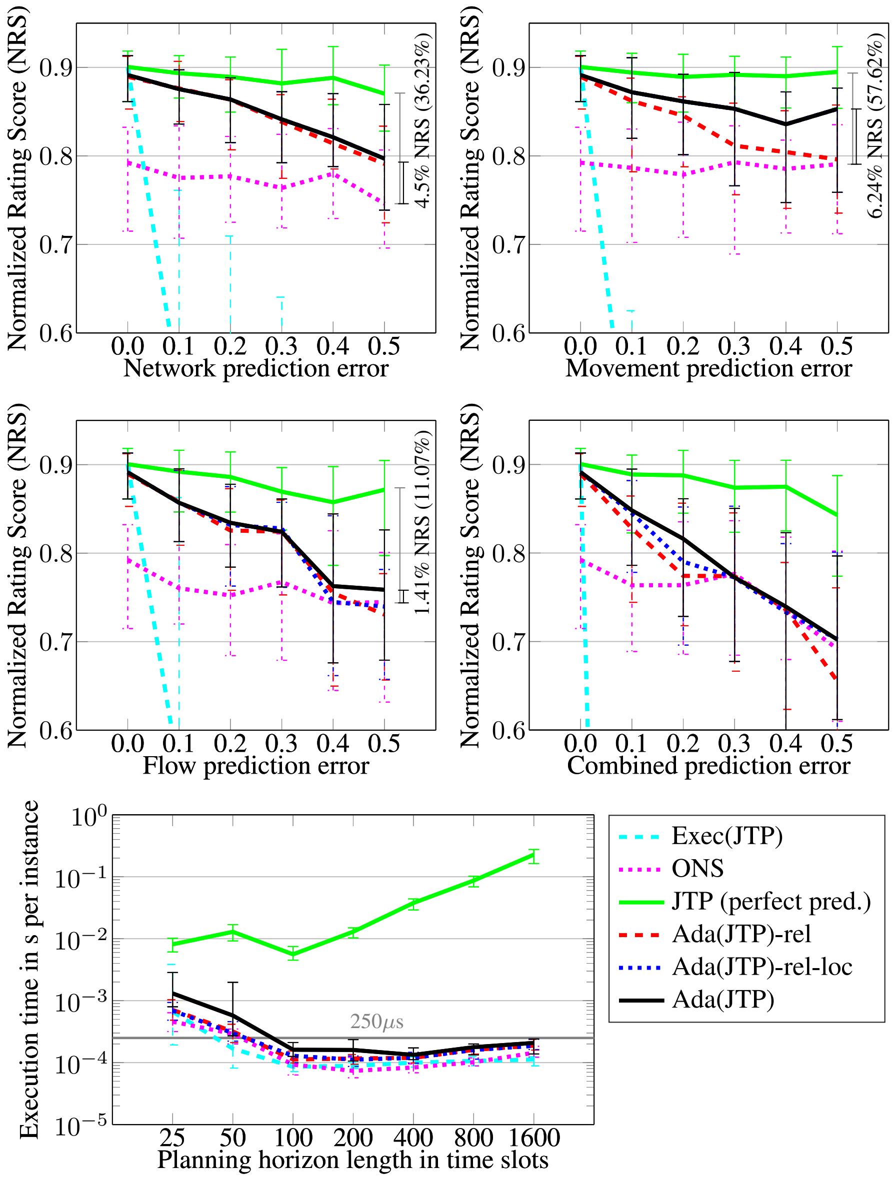


Figure 6: Planners' NRS over SMAPE: movement, network, data flow, combined and execution duration in seconds per instance

sue. The performance loss from movement prediction errors is even less significant than for the network prediction error. It still reaches a performance surplus of 6.24% NRS over ONS, which represents 57.62% of the margin to the reference JTP. Thus, our mechanisms are able to cope even well with heavy network and movement prediction errors. Accordingly, conserving decisions for network selection and delaying data purposefully with the data release mechanism provide effective means to keep a significant share of the planning performance gain. However, data flow prediction errors (c) impose a tough challenge. According to our second mechanism Ada(JTP)-rel-loc (dotted blue), unplanned data is transmitted opportunistically. Furthermore, the adaptation transmits data, for which the desired transmission times change, partially opportunistic with an error dependent threshold. Since we cannot treat new nor canceled data transmissions, the effect of this error handling is rather small. However, while the above-mentioned mechanisms drop at the level of ONS or even below, the final mechanism Ada(JTP) (solid black) is able to keep a performance benefit of 1.41% NRS even for strong data flow prediction errors, which corresponds to 11.07% of the margin between ONS and JTP. Finally, we combine the prediction errors in the last graph (d). A value of 0.2 represents a prediction error of 0.2 for each error type at the same time. The performance loss from the three error types nearly seems to sum up and lead to a convergence to the performance of ONS at a combined error of 0.3 for the final adaptation approach Ada(JTP).

Unlike the pure execution or the partial adaptation models, our final adaptation model never falls significantly below the performance of ONS. This confirms the validity of our designed mechanisms for following a transmission plan and allowing opportunistic allocation. Furthermore, for small and medium prediction errors, our adaptation mechanism is able to preserve a major share of the performance surplus that Joint Transmission Planning with strategic time-network selection promises.

The last graph in Figure 6 (e) shows the execution time per instance over the planning horizon length. We expect a performance-optimized version of our approaches to reach similar execution times on automotive target hardware. Except JTP, all approaches are responsive online methods, which treat transmission only for the next time slot. Hence, we normalize them by the number of time slots. After a first initialization overhead, their average execution time per time slot sinks below 250 microseconds on the long run. In contrast, JTP always plans the complete time horizon. Hence, its execution time rises linearly with the number of time slots. This gives motivation for the following interaction concept between JTP and our adaptation Ada(JTP): After a long-term planning of JTP, the plan is implemented using the introduced adaptation algorithm Ada(JTP). As soon as certain prediction error levels are reached, e.g. through user interaction, unexpected movement or network characteristic changes, planning through JTP should be triggered in the background to update the transmission plan using fresh prediction values. After initialization of the new instance of Ada(JTP), it takes over the data allocation from the previous instance. Thus, heavy prediction errors can be treated within about a second, while reaction on small and moderate unexpected events happens within less than a millisecond through our novel transmission plan adaptation mechanism. This concept unlocks the demonstrated benefits of a strategic time-network selection for application in reality.

## 5. Related Work

The topic of transmission planning covering strategic time-network selection is barely investigated so far. Existing work in transmission time selection reduces network selection to the WiFi-preferred principle and application QoS satisfaction to holding a deadline [8, 6, 9]. In contrast, network selection approaches with detailed application QoS models do not consider the time dimension [5, 10]. Due to these simplifications, their execution time is small enough to apply a continuous re-planning. An adaptation of plans is not required and a handling of prediction errors gets obsolete. Nevertheless, we can learn from Bui et al. [9] that it is beneficial to separate long-term and short-term mechanisms in transmission planning. However, they apply this concept to prediction only but not to the planning itself. Furthermore, it is in the nature of online network selection to apply light-weight algorithms for fast reaction to environmental changes [11]. We apply this principle also to our adaptation. The fact, which distinguishes our adaptation concept from existing work, is that we use information extracted from a long-term plan in order to control the transmission. Therefore, we develop mechanisms that recognize whether following the plan is inefficient, infeasible or requires modifications, which are applied automatically.

## 6. Conclusion

In this article, we investigate how connected vehicles can use heterogeneous wireless networks more efficiently to satisfy application requirements best possible. We present our approach of *strategic time-network selection* using transmission plans and demonstrate its significant benefits over state-of-the-art concepts for the connected vehicle scenario, outperforming them by up to 18%.

However, in this paper, we identified that a direct execution of these plans is ineffective due to its inability to react to environmental changes. To this end, we designed a novel transmission plan *adaptation* scheme that employ an opportunistic online transmission algorithm, ensuring that the approach implements the plan whenever possible and adapting parts of the plan if new or alternative opportunities appear to be better in the *actual* environment. The performance of the strategic time-network selection complemented by the adaptation shows a substantial performance gain of up to 10% over state-of-the-art approaches for small and medium prediction errors. With rising prediction errors, it converges towards the performance of the opportunistic approach and, unlike direct execution, does never fall significantly below its performance. Conclusively, the adaptation approach exploits the additional optimization potential from transmission planning using prediction for strategic time-network selection without the risk of performing worse than state-of-the art approaches. Thus, using the presented approach, connected vehicles can benefit from prediction data in order to improve their perceived Internet access performance.

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and the simulation setup for reproduction of the results are available at `https://www.kom.tu-darmstadt.de/~rueckelt/scheduling/`.

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