Toward Dynamic Frequency Planning for Reliable Connectivity in Mobile 6G in-X Subnetworks

Valentin Thomas Haider, Fidan Mehmeti, and Wolfgang Kellerer
Chair of Communication Networks, Technical University of Munich, Germany
{firstname.lastname}@tum.de

***Abstract*—Within the research for the sixth generation of mobile networks, so-called in-X subnetworks (SNs) were proposed to support services with extreme performance requirements in geographically confined areas. To facilitate efficient spectrum usage and reliable connectivity within in-X SNs, adequate dynamic frequency planning methods for managing interference must be developed. This work provides background on in-X SNs and reviews related work on frequency planning and interference management. The problem of minimizing SN reconfigurations is identified as a key objective, while it is not addressed in the literature to date. Thus, the trade-off between minimizing subband usage and reducing SN reconfigurations is analyzed using both an already existing basic and a newly proposed advanced interference model. Preliminary results highlight how interference modeling and knowledge of future interference scenarios affect optimization outcomes, and future research directions toward dynamic frequency planning for in-X SNs in real 6G systems are discussed.**

***Index Terms*—Frequency Planning, Multi-Objective Optimization, Resource Allocation.**

I. Introduction

Throughout all generations of mobile communication networks, frequency planning has been regarded as a crucial task for their successful deployment and management [1]–[4]. There are two main reasons for this: First, the frequency spectrum available for radio communications is inherently scarce [1]. This makes spectrum reuse essential for achieving high spectral efficiency [4]. Second, spectrum reuse can cause interference, which makes effective frequency planning necessary to mitigate or prevent co-channel and adjacent channel interference, thereby enabling stable and reliable communication links while efficiently using available resources [3], [4].

Within current 6G research, so-called in-X subnetworks (SNs) are envisioned to constitute a key technology for providing ubiquitous network connectivity [5]–[9]. Possible deployment scenarios for these SNs include, e.g., industrial environments, vehicles, or drones to facilitate communication between users in geographically confined areas like factories, cars, or dense urban areas. The use-cases that are envisioned for in-X SNs are, e.g., intra-vehicle sensor-actuator communication [6], [9], in-body networks for health monitoring [8], [10], or robot control in industrial environments [5], [9], [11].

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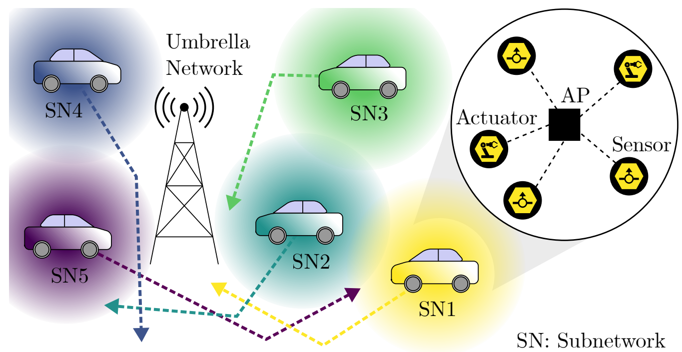

Fig. 1. Illustration of mobile 6G subnetworks and their trajectories with the subnetwork APs deployed in vehicles connecting sensors and actuators.

Thereby, the goal of SNs is to provide high data rates, ultra-low latencies, and high reliability and availability. An illustration of mobile in-vehicle SNs within the coverage area of a so-called *umbrella* or *parent network* is shown in Fig. 1.

To enable these services and meet their extreme performance requirements, adequate frequency planning methods must be developed [9], [11], [12]. This becomes even more critical as most in-X SNs are envisioned to be mobile. As a result, frequency planning cannot rely on static configurations. Instead, the allocation of frequency subbands must be dynamic to adapt to varying interference scenarios caused by evolving SN positions, while ensuring efficient spectrum usage.

However, dynamic (re-)allocation of subbands for interference management introduces *SN reconfigurations*, which can lead to network downtimes due to reconfiguration delays and cause signaling overhead both between the SN and the umbrella network as well as within the SN. Therefore, dynamic frequency planning methods for 6G in-X SNs must fulfill two main objectives: (1) manage inter-SN interference and external interference from stationary Base Stations (BSs), and (2) minimize SN reconfigurations.

This paper outlines recent [13], ongoing, and planned research toward dynamic frequency planning for reliable 6G in-X SNs. First, background on SNs is provided, and related work on frequency planning and interference management is discussed. Subsequently, the trade-off between minimizing frequency subband usage and SN reconfigurations is examined using both a basic interference model and an enhanced model that more accurately represents interference between SNs.

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II. Background and Related Work

In general, SNs can be operated in three different modes: In the *standalone mode*, the SN runs fully autonomously, whereas in the *semi-autonomous* and *connected mode*, the SN can receive control information from its 6G umbrella network, and the SN AP may additionally act as a gateway to the umbrella network [8], [10]. Depending on the operation mode, the allocation of frequency spectrum is either performed in a distributed (SNs in *standalone mode*) or in a centralized (SNs in *semi-autonomous* and *connected mode*) manner.

While distributed resource management allows for fully autonomous SNs, see, e.g., [11], [12], [14]–[19], it generally cannot give any guarantees on interference levels or service quality. These works therefore focus on, e.g., maximizing all SNs' sum rates or minimizing the sum interference-to-signal ratio across all SN links. To achieve these objectives, the authors mainly rely on Machine Learning (ML) approaches like Reinforcement Learning (RL) to select channels based on, e.g., interference power measurements or Received Signal Strength Indicator (RSSI) values [11], [12], [14]–[17]. There exist only a few papers relying on heuristic approaches for distributed decision making [18], [19]. To provide guarantees on interference levels or service qualities, centralized resource management is required for SNs operating in the *semi-autonomous* or *connected mode*.

Previous work on centralized subband allocation has employed Graph Neural Network (GNN)-based [12] or Deep Neural Network (DNN)-based [20] methods, or a sequential iterative algorithm [21]. These works try to minimize the number of interfering SNs, maximize the SNs achieving their target data rates, or minimize the interference-to-signal ratios of the SNs given a limited amount of resources.

Furthermore, the problem of joint power control and subband allocation has been investigated for special use cases. A distributed resource and power selection scheme for control system SNs with the objective of minimizing an Age of Information (AoI) violation probability is presented in [22]. In [23], the long-term control costs of SN-controlled plants are minimized using a decentralized power and subband allocation policy, while the authors of [24] maximize the transmission reliability of eXtended Reality (XR) video frames in In-body Subnetworks (IBSs) using a multi-agent based power control and subband allocation policy. Maximizing the minimum channel capacity per SN for scenarios with limited sensing or channel state information is the objective of [25]. To this end, a distributed RL-based allocation method is proposed. In [26], the authors present a centralized DNN-based solution for maximizing the average spectral efficiency. Lastly, the authors of [27] consider both inter-SN and external interference and propose a gradient descent-based power and subband allocation scheme for this scenario.

While the previously discussed works consider mobile SNs, i.e., varying interference scenarios, and thus optimize resource allocation at different time instances, *SN reconfigurations*, i.e., changing an SN's allocated frequency spectrum from one time step to another, have not yet been considered. Due to the reconfiguration delay and the signaling overhead, an SN reconfiguration can, however, have a significant impact on the service availability and reliability within an SN. Thus, in [13], we have studied the problem of dynamic frequency subband allocation to mobile in-X SNs with the objectives of *minimizing SN reconfigurations* and *spectrum usage* while guaranteeing interference-free operation of all SNs. Thereby, depending on the SNs' positions, SNs were classified as either interfering or non-interfering (binary interference classification). The subband demand of each SN was modeled as an integer value, allowing for different allocation granularities. Furthermore, we have investigated how knowledge of future SN positions and thus knowledge about future interference scenarios, which can be available in the case of autonomous vehicles, can influence the optimization objectives. Our results reveal a clear trade-off between the conflicting objectives of minimizing SN reconfigurations and spectrum usage and indicate that greater knowledge of future positions enables further minimization of both objectives.

III. Enhanced Interference Modeling

To advance the work presented in [13], an enhanced and more realistic model for representing interference relations between SNs is proposed. Specifically, in this model, the experienced interference of an SN is expressed as a continuous power parameter, which can be derived from a suitable channel model. Then, the previously binary interference constraint, where two SNs that interfere cannot be allocated overlapping frequency spectrum, is replaced by an interference threshold constraint, where the experienced interference of an SN from all other SNs that are allocated the same subband must not exceed a threshold I^{thr}. Mathematically, this interference constraint is written as

$$i^b_{s,b}(t) = \sum_{\substack{q \in \mathcal{S}(t),\\ q \neq s}} i^{sn}_{q,s}(t) \cdot a_{s,b}(t) \cdot a_{q,b}(t) < I^{thr} \; \forall b \in \mathcal{B} \quad (1)$$

where $i^b_{s,b}(t)$ is the experienced interference power in subband b for SN s, the variable $i^{sn}_{q,s}(t)$ is the interference power caused by SN q at SN s, and $a_{s,b}(t)$ indicates whether subband b is allocated to SN s in time step t. For a single SN s, the constraint must hold for all subbands b that are allocated from the set of available subbands $\mathcal{B}$. Naturally, constraint (1) must hold for all SNs from the set of SNs $\mathcal{S}(t)$ and for all time steps $t \in \mathcal{T}$ that are considered during the optimization, i.e., the time steps for which the interference relations between the SNs are known. For the complete mathematical formulation of the multi-objective optimization problem for minimizing frequency subband usage and SN reconfigurations, the reader is referred to Section III of [13], with the exception that the interference constraint (1d) is replaced by the new interference threshold constraint formulated in (1).

A. Preliminary Evaluation

To evaluate the difference between the basic binary interference model and the more realistic model proposed in this

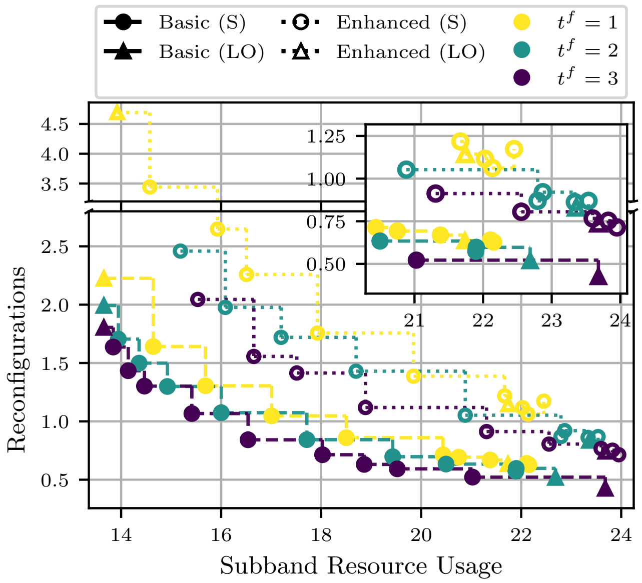

Fig. 2. Average number of reconfigurations and subband usage for 1000 time steps. Results are obtained for scalarization (S) with weights for the reconfiguration objective ($f_2(t)$ in [13]) in $w_{f_2(t)} \in \{1, 1.5, 2, 3, 5, 7, 9, 11, 15\}$ and for lexicographic ordering (LO) with the corresponding priorities of the two objective functions for future knowledge $t^f \in \{1, 2, 3\}$.

work, the exact same input data as in [13] is used. Mobility traces for vehicles are generated using a Manhattan Mobility Model, and interference powers are calculated using the LOS path loss formula for the Indoor Hotspot (InH) scenario defined in [28]. For the binary interference classification, a Signal-to-Interference-plus-Noise Ratio (SINR) cut-off value of 10 dB is applied. Since the distance between the serving SN AP and the sensors and actuators is fixed at 2.5 m within the vehicle, this SINR value can be directly converted to an interference threshold of $I^{thr} = -36.16\,\text{dB}$ for evaluating the enhanced interference model.

In Fig. 2, the optimal results in the form of Pareto curves are shown for both the basic and the enhanced interference model. For each interference model, three Pareto curves are presented, corresponding to knowledge of future interference scenarios one, two, or three time steps ahead $\left(t^f \in \{1, 2, 3\}\right)$. The multi-objective optimization problem was solved by either forming a single scalarized objective function with weight 1 for the subband usage objective and weights in $\{1, 1.5, 2, 3, 5, 7, 9, 11, 15\}$ for the reconfiguration objective, or by employing lexicographic ordering, i.e., strictly prioritizing one objective function over the other.[1,2]

First, it is observable that the Pareto curves of the basic interference model dominate those of the enhanced interference model. This results from the fact that, in the basic model, SNs that interfere with each other but still achieve SINR values above 10 dB on a per-link (isolated) basis are not regarded as interfering, whereas in the enhanced model, such interference contributes to the total experienced interference of an SN in a subband. Therefore, the results obtained for the enhanced interference model are generally worse, as they account for the aggregated interference from a global network perspective.

Second, the value range of subband resource usage is almost identical for the basic and enhanced interference models. In contrast, the range between the minimum and maximum number of reconfigurations is substantially larger for the enhanced model. For example, with $t^f = 1$, the maximum number of reconfigurations is $4.42\times$ the minimum in the enhanced model, compared to $3.50\times$ in the basic model. This underlines that the trade-off between subband resource usage and SN reconfigurations remains clearly present, and becomes even more evident when using a more realistic interference model.

Third, for both the basic and enhanced interference models, greater knowledge of future interference scenarios leads to improved optimization results. The Pareto curves for $t^f = 1$ are dominated by those for $t^f = 2$, which in turn are dominated by the curves for $t^f = 3$. For the enhanced model, for a comparable subband resource usage of approximately 16.5 ($w_{f_2(t)} = 2$ for $t^f = 1$ and $w_{f_2(t)} = 1.5$ for $t^f = 3$), the average number of reconfigurations is reduced by 30.97 %. Similarly, increasing t^f from 1 to 3 decreases the minimum achievable average number of reconfigurations by 30.19 %.

Fourth, while increasing t^f reduces the number of SN reconfigurations at the cost of higher average subband usage, the minimum achievable subband usage remains unaffected by increasing t^f (see the results for lexicographic ordering). The reason is that the subband usage objective is time-independent and thus does not benefit from additional knowledge. Reconfigurations, however, can still be reduced with greater t^f even when prioritizing subband usage.

Finally, in the zoomed region of Fig. 2, some scalarization results with high reconfiguration weights achieve a slightly lower number of reconfigurations than the lexicographic ordering results that prioritize reconfigurations. Although this may appear counterintuitive, these results arise because the subband allocation from the current time step is used as the starting point for the optimization in the subsequent time step. This can lead to allocations in earlier time steps that, while not optimal locally, result in later allocations with a slightly lower average number of reconfigurations.

B. Open Research Questions

Minimizing the sum of all SN reconfigurations is a simplification of what would actually be desired in a real system, where the goal is to minimize each individual SN's reconfigurations. Focusing solely on the sum can produce extreme cases in which one SN undergoes many reconfigurations while the others experience almost none. Although such solutions may improve the overall optimization objective, they are undesirable in practice. Therefore, the optimization problem will be reformulated to include a separate objective function for each SN to minimize its reconfigurations. Subsequently, alternative

[1]For more information on scalarization and lexicographic ordering, the reader is referred to the discussion in [13] and the references therein.

[2]Due to the computational complexity of the optimization problem, it was not possible to obtain results for $t^f \in \{2, 3\}$ for the enhanced interference model when prioritizing reconfigurations in a reasonable amount of time.

strategies such as dynamic (time-dependent) weight assignment or dynamic lexicographic ordering, e.g., based on the experienced number of reconfigurations, will be investigated to compare both the average numbers of reconfigurations and their coefficient of variation for static and dynamic approaches. In addition, new heuristic algorithms will be developed to achieve near-optimal results in polynomial time while handling the enhanced interference constraint (1).

IV. Conclusion and Future Research Directions

This paper presents a path toward frequency planning for reliable connectivity in mobile 6G in-X SNs. Related work on subband allocation and power control for interference management was reviewed, discussing different centralized and distributed solution approaches. The problem of SN reconfigurations, which has not been treated in the literature, is identified as a key challenge for enabling reliable connectivity through dynamic frequency planning. Therefore, the multi-objective problem of minimizing subband usage and SN reconfigurations while managing inter-SN interference, first introduced in [13], was revisited, and an enhanced, more realistic interference model was proposed. Preliminary results revealed that the overall optimization results for the enhanced model are worse than for the basic binary model. Nevertheless, the trade-off between the two objectives remains evident. Minimizing reconfigurations for each individual SN is identified as the primary next step for advancing the optimization problem.

Looking ahead, several other open problems and research questions must be addressed to enable dynamic frequency planning in real 6G in-X SN systems:

- In systems where the frequency spectrum is limited, what is the trade-off between minimizing reconfigurations and experienced interference for each individual SN?
- How does incorporating power control influence the objectives, and to what extent can the transmitted power be varied while maintaining a high level of signal quality?
- How does uncertainty in predicting future interference scenarios affect the optimization results?
- Can alternative solution approaches, such as GNNs, capture the time-dependency of the problem and outperform heuristic methods?

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