A Predictive Approach for Transport Protocol Multi-Connectivity Scheduling

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Abstract— **In this era of 5G and beyond, Non-Terrestrial Networks (NTN) plays a pivotal role in providing ubiquitous connectivity. Hence, it is essential to maintain connectivity with NTN, although a device is already connected to a Terrestrial Network (TN). The ideal approach would be to handle this at transport protocol layer as independent networks are involved. Establishing Multiple-Paths (MPs) between NTN and TN by means of MPTCP is a promising approach to realise this. Both the networks have different data rate and the available capacity, which varies over time based on the traffic demand. In this work, we start by presenting a solution to predict the traffic demand on NTN link based on federated Kolmogorov Arnold networks (fed-KANs). This predicted traffic demand is then used as an input to the MP scheduler to efficiently utilize the bandwidth available on both the NTN and TN. The goal is to minimize the data file transfer time and increase throughput. The proposed scheduling mechanism reduces the file transfer time compared to benchmark MP schedulers and achieves higher aggregated throughput. This shows that a scheduling mechanism with the knowledge of expected traffic demand performs better than classical schedulers which do take this into consideration.**

Keywords—Multi-Connectivity, MPTCP, Scheduling, 3GPP, NTN, AI, KANs

I. INTRODUCTION

NTNs are considered as an important technology in 5G and 6G standardisation extending terrestrial networks (TN) to provide ubiquitous coverage and, generally, improve the Quality of Service (QoS). Parallel links can be used for increased throughput, lower latency, or as fall-back increasing resilience. For this, a User Equipment (UE) can connect via both systems (TN and NTN) for communication. In order to optimally use the available resources on both links multi-connectivity, technologies can be utilized. In [1] an overview can be found on using multi-connectivity at different layers of the communication protocol stack. Our focus is on the transport layer using Multi-Path (MP)TCP, MPQUIC, as standardized by 3GPP's Access Traffic Steering, Splitting and Switching (ATSSS). ATSSS is an optional part of the 3GPP standards to connect a non 3GPP technology and a 3GPP technology to the 5G core, described in 3GPP TS 24.193 [2] and TS 23.501 [3]. However, in our setup we are assuming a 5G system in the TN as well as for the NTN system, with an extended ATSSS functionality supporting this.

In ATSSS, steering refers to selecting for the user traffic, the best service link for a flow with linked QoS-type. Switching means a handover to the second link in case of interruptions. Splitting allows to distribute the traffic between both links for load balancing. According to the standard [3], five modes are specified:

- active-standby: one access network is defined as main, the other as active-standby. In case the main is not available, traffic is steered towards the stand-by access.
- smallest delay: the access network with the smallest round-trip time (RTT) is used.
- load balancing: the flow is steered across both the 3GPP access and the non-3GPP access, with a given percentage.
- priority based: the UE uses the access with high priority unless it is congested or unavailable, then the traffic is split over both the access networks
- redundant: traffic is duplicated on both access networks. Optionally a primary access can be selected in which case the primary must be used for all packets, the secondary may be used to send the duplicate packets.

Each of these modes can be linked to a dedicated scheduling strategy. In our setup a UE connects via TN and via NTN to the 5G Core using an ATSSS connection, e.g. MPTCP or MPQUIC. In case of MPTCP this would be via two TCP sockets. The scheduler needs to decide where to route a packet depending on the mode. In this paper, we propose the use of a predictive scheduler with the knowledge of future traffic demand on NTN link to distribute data traffic on both TN and NTN links. A predictive model based on federated Kolmogorov Arnold networks (KANs) has been used for NTN link traffic forecasting. To the best of our knowledge, this is the first work in which the traffic forecasting leveraging KANs has been used for the scheduling mechanism for MPTCP.

A good overview of scheduling and testing of packet scheduling in MPTCP can be found in [4]. The authors point out the potential benefits and research opportunities such as a bottleneck-aware end system, and packet meta-scheduling that selects a fitting one from a range of schedulers. However, they do not include approaches including predictive means or ML-algorithms.

Traffic prediction based on historical data falls within the scope of time series forecasting, which is a traditional problem present in a wide range of fields. Recently, an innovative solution specifically tailored to traffic forecasting has been conceived in [5]. The proposed predictive model leverages KANs. KANs represent a new paradigm for neural networks that contrasts with traditional multi-layer perceptron based neural networks, as detailed in [6]. The main distinctive feature of KANs is that traditional linear weights are replaced with spline parametrised univariate functions, enabling the network to learn activation patterns dynamically. These learnable functions allow KANs to outperform conventional MLPs in a real-world satellite traffic forecasting task. The work presented in [5], [1] highlights that more accurate results are achieved with considerably fewer learnable parameters.

Following the guidelines reported in [7], the forecasted traffic obtained with KANs can be used to determine the number of requested physical resource blocks (PRBs). This outcome is essential for strategic planning of resources. For instance, accurate forecasting is needed to dynamically allocate bandwidth in 5G networks so as to satisfy future traffic demands. The application scope also includes scheduling for load balancing between terrestrial and non-terrestrial networks. The interplay between the predictive algorithm and the scheduling algorithm is detailed in Section II.

Recent research has shown that probabilistic forecasting offers further benefits when planning radio resources. In integrated terrestrial and non-terrestrial networks (TN-NTN), single point methods such as LSTM do not capture the variability of satellite traffic. Some works [8] have shown that probabilistic forecasting models deliver better predictions of bandwidth and capacity requirements and enable operators to quantify uncertainty in resource demands. This has important implications for the standardization of future 6G networks, where accurate and reliable traffic forecasts can reduce over and under provisioning [8].

Probabilistic forecasting is also crucial in the Open RAN (ORAN) context. In [9] [10] authors compared deterministic and probabilistic techniques for PRB load prediction and found that models like DeepAR outperform LSTM and other baselines. DeepAR provides tighter prediction intervals and better captures temporal dependencies, allowing network operators to balance energy savings against the risk of under or over provisioning [9]. These results highlight the need to couple adaptive forecasting models such as KANs with probabilistic methods to support energy efficient scheduling in O-RAN.

This paper is organised as follows. Section II presents the proposed predictive scheduler used in the multi-connectivity scenario. Section III explains the approach used to predict the available capacity on the link. Section IV introduces the test bed used to validate the proposed scheduler. The preliminary results of the simulation are summarised in section V. Section VI concludes the work.

II. PREDICTIVE SCHEDULER

Figure 1 illustrates the inputs and outputs of the predictive scheduler. The first input is the traffic coming from the UE that needs to be scheduled on the TN and on the NTN links via the sockets. Second input is the link capacity predictions. It provides the forecast of the capacity usages based on historical data. Since radio resources are a shared medium only a certain ration can be consumed by a single user. If more users are active during the same time, the system might enter a capacity limit that leads to congestion. Our focus is on the NTN system; hence we use the prediction of the available capacity of one link which is the NTN system. The idea of including the prediction in the scheduling decision is to allow a reaction already before link conditions might make it necessary and with this further improve the QoS performance. Last, input that can be used to form a solid information basis for a scheduler decision is the feedback from the sockets, e.g. congestion state, buffer state, congestion windows, RTT.

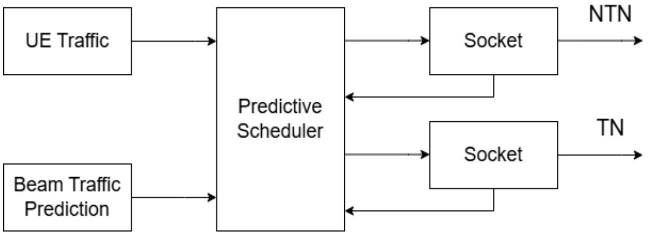

Figure 1: Predictive Scheduler Inputs and Outputs

There are several options for the implementation of the scheduler. While the predictive information would also allow for heuristics or algorithms, we investigate on the use of ML-algorithms. In such case the behavior of the scheduler can be tuned following different modes in line with ATSSS. In Each case the required optimization goal and according reward for the ML-algorithm can vary, as well as the monitored parameters coming from the socket. We see the following main objectives of using ML-algorithms for each mode:

- active-standby: Improve hand-over performance by optimizing the switch-over time
- smallest delay: improve latency by optimizing RTT
- load balancing: try to be close as possible to a given threshold while optimizing data throughput and packet loss
- priority based: prioritize one while optimizing data throughput and packet loss

- redundant: transmit data on both while optimizing reliability and resource consumption (if current conditions allow use only one link)

III. CAPACITY PREDICTION AND SCHEDULING

To address the challenges of decentralized training in satellite networks, the authors extended KANs to a federated learning setting. The Fed-KAN algorithm trains local KANs on edge devices and communicates only spline parameters, achieving a 77.39 % reduction in average test loss compared with federated MLPs [11]. This federated approach reduces communication overhead and improves generalisation, making it well suited for TN-NTN and O-RAN environments where connectivity is intermittent.

Furthermore, the combination of adaptive KANs, probabilistic forecasting and federated learning represents a comprehensive framework for traffic prediction and resource management in next-generation networks. These approaches promise to improve forecasting accuracy, quantify uncertainty and enable dynamic scheduling for both terrestrial and non-terrestrial systems [7] [8].

The predictive scheduler that we are proposing takes this forecasted traffic demand as a primary input for scheduling. The scheduling mechanism in multi-connectivity scenario plays a vital role in the efficiency of the setup. The mode considered here is load balancing where the traffic on the links is optimised. The links have to be utilised smartly in order to split the data packets to make use of the full capacity offered by the links. It should be noted that the MP scheme should not compete with the usual data flow so as not to jeopardise the usual traffic without MP enabled for the traffic flow. One way of tackling this issue is to make use of the traffic demand prediction during the scheduling process. The predictive scheduler should take into consideration only the link capacity available after the utilization of the normal data flows without MP enabled. The traffic prediction from federated KANs approach can be used to achieve this and the predictive scheduler makes use of this information for scheduling the packets on the links.

IV. MULTI-CONNECTIVITY TESTBED

The testbed for testing the Predictive Scheduler has been developed in Mininet [1]. Mininet is a network emulator which creates a network of virtual hosts, switches, controllers, and links. The block diagram of the testbed setup is shown in Figure 2. The file transfer happens from node 1 to node 2 using an MPTCP connection which is used by the apps present on both the nodes for communication. Node 1 has a sender app which creates MPTCP sockets and sends the data packets to the receiver app. Node 2 listens on an MPTCP socket to receive the data packets. The sender app sends the packets to this socket. There are two links between the nodes, one using Terrestrial Network (TN) and another Non-Terrestrial Network (NTN). So, the considered scenario has heterogeneous links with different characteristics.

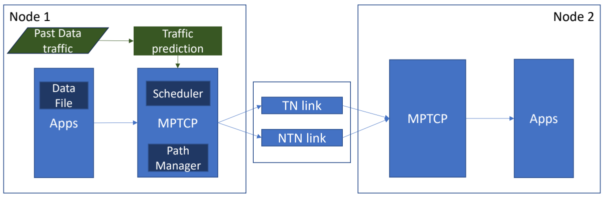

Figure 2: Test bed block diagram

Then, the MPTCP module consists of two main components: path manager and packet scheduler [13]. The path manager is responsible for creating sub flows between the nodes for establishing multi-connectivity. Once the sub flows have been created, the packets are sent across these links. The scheduler has different strategies to send packets through the sub flows. The most common algorithms are Round Robin (RR) and Redundant scheduling (RS). Round Robin divides the packets equally while redundant strategy duplicates the packets on both links. The ideal approach depends on the link characteristics. Round Robin algorithm is suitable for scenarios in which both the links have similar characteristics (i.e., homogeneous networks), while redundant scheduler is mostly used in scenarios with high Packet Loss Rate (PLR).

The TN link characteristics are based on the traffic pattern of a moving train. Hence, the TN link characteristics illustrates the typical traffic pattern of train passengers. But, the bandwidth available for the file transfer varies based on the traffic demand that changes based on the time of the day. During peak hours the file transfer occurs at a reduced data rate. The dataset used for the simulation is from the open data sets deliverable [14] of 5G-STARDUST project. In the case of NTN link, available link capacity changes during the day in addition to changes in link characteristics based on the relative movement of the satellite with respect to the ground node. The NTN characteristics have been obtained from 5G-system simulations using the channel models presented in [15][12]. The throughput of a LEO constellation with altitude of 600km has been modelled and simulated and the throughput over time has been determined. This is used to tune the NTN link performance in Mininet. Additionally, we consider the data rate requests from other users based on real system data as presented in [5], i.e. we see how much capacity in percentage is consumed at a given point in time and add this limitation to the link for the user.

The predictive scheduler receives the current TN link capacity and the forecasted NTN link capacity at a given instant. Then it calculates the share of the total traffic that each link can support. The incoming traffic data packets is scheduled on each sub flow based of the fraction of the total traffic each link can support. Hence, the scheduling mechanism takes into account the capacity in the immediate future which can change over the whole duration of the file transfer.

The scenario considered is a rural area where both TN and NTN can provide connectivity based on the traffic demand. The usual traffic demand over the NTN link has been used to predict the future traffic demand. The goal of the predictive scheduler is to maximize the throughput so as to minimize the

Figure 3: File transfer time

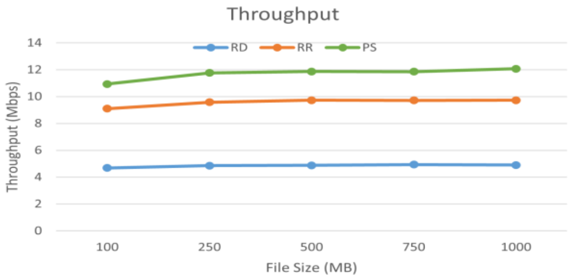

Figure 4: Average throughput

file transfer time between the nodes. In the test bed, we have used the predicted bandwidth available for non-terrestrial links using the federated KAN approach mentioned in section III.

V. PRELIMINARY RESULTS

In this section, we compare the performance of different MPTCP schedulers. The link characteristics used for all the different algorithms remain the same. The schedulers compared here are Round Robin, redundant and predictive schedulers. The data file size that is transferred is from 100 MB to 1 GB. The data file is packetized and sent continuously by the sender app present on node 1. The packets are scheduled on the sub flows created, as per the different algorithms taken into consideration. The receiver app present on node 2 listens on both sub flows and reorders the packets on both the sub flows to receive the entire data file.

The time to transfer the data file for different file sizes is shown in Figure 3. The redundant scheduler (RD) consumes more time than both Round Robin (RR) and Predictive Scheduler (PS). This was expected as the packets are duplicated on both the links and in effect doubles the number of packets needed to send the file. Round Robin scheduler consumes lesser time compared to redundant approach as the packets are split between the sub flows. But this split is performed by the scheduler without any knowledge of the channel characteristics. The packet flow is completed on the sub flow with higher data rate ahead of the sub flow with lower data rate. Predictive scheduler takes the least amount of time to transfer the packet as the scheduling process takes into consideration the available channel capacity over both the links. Each sub flow is assigned packets based on the available bandwidth for transmission. This results in non-proportional splitting of traffic between the sub flows utilisation the difference in data rate between the sub flows. The proportion of traffic assigned to each sub flow is determined by the current bandwidth availability for TN and the predicted bandwidth availability for NTN.

The average throughput achieved by the different algorithms is shown in Figure 4. The throughput achieved by different algorithms stays fairly constant for different file sizes. This is because the average capacity over a period of time remains the same. The predictive scheduler has the highest throughput due to proportional scheduling that utilises the maximum available capacity on both the links. In the case of redundant scheduler, the multi-path throughput cannot be higher than the individual sub flow data rates. This is because the throughput is calculated based on the size of the data file being transmitted. Since redundant scheduler duplicates the data packets, the throughput cannot be higher than the data rate of the slower sub flow.

VI. CONCLUSIONS

In this work, we have presented a test bed to compare the performance of different MPTCP schedulers namely, redundant, round robin and predictive scheduler using federated KAN approach. Multi-connectivity has been achieved by establishing two sub flows, though a non-terrestrial link and a terrestrial link. The predicted traffic demand was used to forecast the network link capacity for NTN link. Secondly, we have shown how this predicted link capacity can be used an input for predictive scheduler for assigning packets to the sub flows. The simulation results show that this approach performs better than traditional schedulers namely, round robin and redundant schedulers. The performance of the schedulers has been evaluated based on the time needed to transfer files of different sizes from one node to another using MPTCP.

In the future, the predictive scheduler would be extended to consider more parameters for the scheduling mechanism. In this study, we have used only the available data rate for the scheduling process. The link latency and PLR can also be used as a parameter to tune the predictive scheduler. Socket parameters like round trip time, number of retransmissions can help to this regard. Although the scenario considered in the testbed is a direct scenario with multi-connectivity connection established between the end nodes, it would be also interesting to analyse the performance of the system in the case of indirect scenario. In an indirect scenario, an intermediatory node can receive the packets from the UEs without MP enabled. This intermediatory node can open MP connections to the destination thereby eliminating the need to have MPTCP module on all the UEs. This is particularly useful in scenarios where the UEs do not have MP capability.

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