Functional Split of In-Network Deep Learning for 6G: A Feasibility Study

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Abstract—In existing mobile network systems, the data plane (DP) is mainly considered a pipeline consisting of network elements end-to-end forwarding user data traffics. With the rapid maturity of programmable network devices, however, mobile network infrastructure mutates towards a programmable computing platform. Therefore, such a programmable DP can provide in-network computing capability for many application services. In this paper, we target to enhance the data plane with in-network deep learning (DL) capability. However, innetwork intelligence can be a significant load for network devices. Then, the paradigm of the functional split is applied so that the deep neural network (DNN) is decomposed into sub-elements of the data plane for making machine learning inference jobs more efficient. As a proof-of-concept, we take a Blind Source Separation (BSS) problem as an example to exhibit the benefits of such an approach. We implement the proposed enhancement in a full-stack emulator and we provide a quantitative evaluation with professional datasets. As an initial trial, our study provides insightful guidelines for the design of the future mobile network system, employing in-network intelligence (e.g., 6G).

Index Terms—Artificial Intelligence, In-Network Computing, Blind Source Separation, Data Plane Enhancement, 6G

I. Introduction

With the advent of network softwarization and 5G, the mobile network system consists of a control plane (CP) and a data plane (DP). CP serves the purposes of access control, security, handling service requests, policy/charging, etc.; DP consists of network resource elements to deploy network services commanded by CP. Before 5G, CP and DP were tightly coupled, in vendor-specific hardware devices.

5G decoupling allows CP and DP to evolve separately and flexibly by Network Function Virtualization (NFV) and Software Defined Networking (SDN) enablers of network softwarization. Currently, both CP and DP Network Functions (NFs) can be fully virtualized, interconnected as software components in virtual chains, deployed wherever network resources are available.

Recent development in programmability has opened the way for in-network intelligence, which is going to be a key aspect of future 6G networks. P4 language is used in softwarization and its performance is nearly equivalent to

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those traditional vendor-specific products. Examples can be found in model training [1], distributed database consensus [2], etc. These pioneer works show a chance to bring application services back to operator's networks if the DP becomes fully programmable in the forthcoming 6G.

In this paper, driven by the key importance of artificial intelligence (AI) in various vertical industries, we consider a DP enhancement with in-network deep learning (DL) capability. Specifically, we extend configurable user plane functions (UPFs) with a shredding deep neural network (DNN) after modeling training to support in-transit inference services over the extended UPFs deployed in the DP. In order to exemplify the benefits of such an enhancement in DP, we take Blind Source Separation (BSS) problem as a case study. A BSS problem is a mixture data separation problem having many realistic applications e.g., audio analysis, natural language processing, speech recognition, etc. It is representative of a set of typical inference problems that can be solved by DNN-based approaches. We expect that these will occupy the majority of future applications in 6G.

The unique features of our work are as follows. First, we consider DP for DNN inference tasks, complementary to model training problems widely studied in the literature [1]. Secondly, our problem is a special type of distributed AI problems as the inference job has to be done in sequential order over the extended UPFs of a forwarding path in DP. In other words, our problem has to take the order of UPFs into account when designing a DNN split-and-deployment strategy. In contrast, usual distributed learning problems do not have such a constraint. Last but not least, the DP enhancement also requires modifying the counterpart CP procedures/interfaces. In summary, our contributions are briefly listed as follows:

- We enhanced DP with in-network DL capability in order to support popular DNN inference application services for end-users. Specifically, We proposed DNN split strategies in order to realize a progressive data processing for AI inference tasks; accordingly, extended CP interfaces and procedures are introduced as well;
- We took a BSS problem as an example to demonstrate how UPFs can be enhanced with accommodating split DNN. Particularly, we converted a monolithic convolutional neural network (CNN) Conv-TasNet [3] into a split version that can be deployed on the extended UPFs;
- We implemented our proposed solutions in a full-stack

emulator–Communication Networks Emulator (ComNetsEmu). We compared with its original monolithic version and the latest non-DL-based solution [4], the evaluation results based on a professional dataset confirm the benefits of the DP intelligence enhancement.

To the best of our knowledge, we are not aware of similar works in the literature. In addition, our work well aligns with 3GPP prospective work items for the upcoming 5G Release 18, targeting to support AI applications, and the design of future 6G networks. Our work also provides insightful guidelines on the impact of AI on the design of open programmable networks in 6G.

The rest of the paper is organized as follows. First, the related works on in-network DL are introduced in Section II. Section III describes the general strategy for DL enhancement. After that, a BSS problem is used to showcase the proposed scheme in Section IV. Section V covers the full-stack implementation, the quantitative evaluation, and in-depth discussions about our measurement results. Finally, Section VI concludes our contributions and points out future research aspects.

II. RELATED WORK

This section introduces the related works on programmable network devices and in-network DL.

A. Programmable network devices

Network softwarization technologies decouple the CP and DP structure of the network to make in-network computing possible. One of the main advantages of this is that the network endpoints (e.g., servers) suffer from reduced computing power as the workload is offloaded to the network [5].

The drive for programmability of network devices has a long history, such as Protocol-Independent Switch Architecture (PISA), smartNIC, etc. With the advance of SDN, Virtualized Network Functions (VNFs) are interconnected through the underlying infrastructure network as containers, virtual machines, or natively as bare-metal. This allows the creation of an Service Function Chain (SFC) that performs the required computation on the physical devices.

On this basis, P4 – a high-level language to configure programmable network devices – was proposed. The P4 compiler translates P4 programs into code that runs on the underlying switches. Thus, P4 serves as a common interface between SDN controllers and programmable network devices [2]. These trends stimulate the concept of in-network DL, which naturally fits into an edge-cloud continuum within a common framework integrated compute-network capabilities.

B. In-network DL

Within the broad area of in-network DL, there have been several streams of research. One stream of research focuses on enabling DNN training by using distributed learning. [1] supports in-network aggregation to enable sharing switch resources across training jobs. [6] considers the overhead issues of distributed learning problems. A unified traffic compression

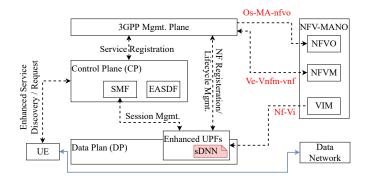


Fig. 1: DL capability enhancements in a 3GPP system. For more information on the interface between NFV-MANO and MP/DP, please refer to the NFV-IFA group specification published by the European Telecommunications Standards Institute.

framework for distributed learning is proposed, which can be easily implemented with most toolkits. In [7], authors explored the challenges and future directions for federate learning on edge devices. In [8], an edge computing-based system is designed to offload the data analysis process from the cloud by deploying the same CNN model to edge nodes and feeding them with different data subsets. These efforts deploy the deep learning network as a whole on a network device, while the end server is mainly responsible for parameter synchronization and updating during the training phase. For training models, these approaches have obvious advantages, such as distributing the training tasks and reducing the data communication volume. However, these advantages cannot be retained in the inference phase, where parameter learning is no longer required.

Another stream has focused on deploying and running DNN in the DP. The authors of [9] transformed the machine learning model for network traffic classification into a P4 language pipeline and deployed it on programmable switches via an Agent Deployer. However, this study focused on the design of the neural network (NN) and the interface between CP and DP. Splitting NNs into multiple VNFs to be deployed is not covered. [10] provides the first open-source implementation of a distributed NN in a programmable DP. This paper is based on the deployment of neurons, however, as DNNs grow increasingly large, the number of neurons explodes much larger than the available network devices, making neuron-based deployment in the network impractical.

While these streams have made important and unique contributions to in-network DL, the need for a splitting strategy to distribute DNNs is becoming more and more intense, especially with today's programmable network devices and increasingly large-scale NN models.

III. IN-NETWORK DL ENHANCEMENT FOR 6G

In this section, our proposed extension on DP is presented, followed by an introduction to the management plane (MP) and CP extension for 6G.

A. DP DL capability extension

According to the reference architecture defined by 3GPP SA2, in core network part, DP mainly consists of UPFs

transporting packet data unit (PDU) sessions. A PDU session represents a QoS-aware connection between a user entity (UE) and a data network located at the edge or in a data center. As mentioned, in existing mobile network systems, UPF acts as a pure networking element, only transmitting bits and bytes in terms of the IP header of a data packet. In order to extend UPF with DL capability, it is equivalent to enhancing UPF with a local DNN component as shown in Fig. 1, which can be configured according to specific applications.

Trivially embedding a DNN is unrealistic because DL is computationally demanding, and it often requires a complex computing architecture (such as dedicated hardware like GPU and large memory). Although the future UPF element will be programmable with compute-oriented resources onboard, its computational power shall be still much less than a Commercial off-the-shelf (COTS) server node. Nevertheless, the size of a DNN is usually huge [11]. Hence, a central challenge is how to split a DNN into pieces that are network element-suitable. Considering this challenge, we propose the following principles when a DNN needs to be split and embedded on several UPFs along a forwarding path.

- Principle-1 proportionally splitting a model: Currently, popular DNNs easily have millions or higher numbers of parameters with dozens of network layers. Unlike a server, a UPF cannot offload the entire model. Splitting a model proportionally can assure that a UPF will not be overloaded;
- 2) Principle-2 avoiding inter-UPF traffic explosion: A DNN transforms raw data into high-dimensional feature representations by convolution or other operations. This process usually accompanies temporal variations of data volume transmitted between layers. To avoid the data volume between two UPFs exploding, it is necessary to split a DNN at the layers whose temporal data volume is small. Note that achieving this objective may contradict to the first one;
- 3) Principle-3 parallelizing local processing and forwarding: Local DL on a UPF requires data and temporal outputs of the last layer of a DNN delivered from the previous UPF. Caching and waiting for the required inputs take time, especially when the path length increases. Hence, parallelizing the underlying forwarding strategy and efficient inter-UPFs interactions should be considered.

Bearing with the three principles above, a generic way to split a DNN can follow the procedures below:

The first step is to analyze the parameter size distribution of the DNN. Following Principle-1, the DNN is divided into multiple neural blocks proportional to the capacities of allocated UPFs.

The second step is to adjust the splitting result from the first step and avoid data explosion splitting points located in between two consecutive UPFs as much as possible, following Principle-2. For example, the authors in [12] use the saddle point of filtering rate to determine splitting points where the amount of temporal data is smaller. This tells us which layer should or should not be a splitting point.

The third step is to analyze the computing logic of neural blocks to avoid waiting for other neural blocks' processing, thus wasting UPF's computing resources. For example, the low-complexity shortcut path of a bottleneck residual block must wait for data from the high-complexity path. With following Principle-3, such processing and forwarding need to be parallelized to avoid caching and waiting. Therefore, the splitting result may be further revised.

B. MP and CP extension

After we introduce the part of DP enhancement, we briefly introduce what has to be done at the MP and CP accordingly for completeness, although this part is not the main focus of this paper.

1) MP extension: MP has to support orchestrating the new type of UPF with DL capability. Specifically, since a DL application usually uses a dedicated DNN model, creation and modification of such a UPF need to involve a service provider, which is not supported in 5G MP. In other words, the existing 5G MP does not allow to configure UPF with an additional processing logic for a particular application service. In order to enable this, as highlighted in red in Fig. 1, the following minimum extensions are suggested:

- Os-Ma-nfvo: Over this interface, an application service provider shall be able to publish a set of in-network computing logic for its application services to NFV-Management and orchestration (MANO) (nfvo);
- Ve-Vnfm-vnf: Virtualized Network Function Manager (VNFM) shall be able to receive the request of deploying a UPF with an in-network computing logic defined by the service provider from NFV-MANO; VNFM prepares a NF description in terms of the resource availability;
- Nf-Vi: A NF description with the service provider's feature is sent to Virtualized Infrastructure Manager (VIM) who will instantiate a VNF instance at the NFV infrastructure.

After the customized UPF is instantiated, the instance will register itself or be identified by the relevant management entity (e.g., the element manager of the network) for *configuration*, *fault*, *and performance managements*. It is also ready for service provisioning with CP. For our case, the extended MP deploys the UPF instances with a split DNN for a DL application service.

- 2) *CP extension:* CP has to support provision a service that is requested by a UE indicating to activate the enhanced feature at the DP (i.e., the UPF with DL capability). This requires a series of updated control flows among existing CP-NFs. At least the two aspects below have to be extended:
 - Service Discovery: As shown in Fig. 1, this happens between a UE and an Edge Application Service Discovery Function (EASDF). An EASDF provides edge application service information that is needed for a UE. The information has to be extended to include whether a requested application service supports the in-network computing feature; after receiving the response from EASDF, a UE can decide if it wants to establish a PDU session over the enhance UPFs;

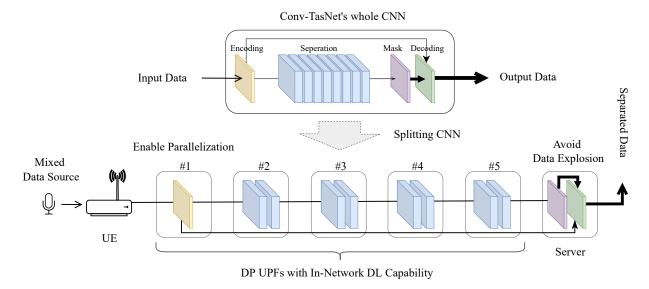


Fig. 2: An illustration of the ultimate splitting of Conv-TasNet. DP path length is five, and every UPF can accommodate maximum of two neural blocks.

• Session Management: As shown in Fig. 1, this happens between a UE and a Session Management Function (SMF) that is responsible for PDU session establishment. SMF has to be extended to support identify, select and configure the new type of UPFs that are enhanced with application-specific processing logic; SMF shall also react to mobility events of the UE for service continuity, Quality-of-Service (QoS) measurement collections and report to other CP-NFs for charging and policy interventions and so on.

In summary, DP and M-/CP enhancements together complete the picture of enhancing in-network DL capability for machine learning (ML) inference application services in 6G.

IV. A CASE STUDY: BLIND SOURCE SEPARATION (BSS) PROBLEM

A. BSS problem

BSS [13] is the process of recovering the source signal from a mixture of observed signals without the aid of information (or with very little information) about the source signals and the mixing process. Since acoustic signals are naturally interfered with, the observed signals need to be separated to understand each source individually. As introduced, BSS is a fundamental data pre-processing technique for numerous acoustic applications, such as audio analysis, natural language processing, speech recognition, etc. It is also promising if such a pre-processing can be accelerated when collected data is being transmitted via a mobile network before arriving at a server end.

BSS problem has been studied for years in the field of signal processing. One of the most successful approaches is Independent Component Analysis (ICA) [13]. Because of its high demand for computational power, ICA is often executed on a powerful server machine. Recently, DL techniques are adopted to solve the BSS problem, as an alternative to ICA

methods. One of the most advanced is a CNN-based Conv-TasNet [3], which is recalled upon next.

B. Conv-TasNet preliminary

Conv-TasNet consists of several convolutional layers as shown in Fig. 2. The input time-domain signal is encoded into the feature space by the convolutional layer at the beginning (marked with yellow). After the first layer, there are eight stacked 1-D convolutional layers as the separation part (marked with light blue) performing the actual data separation jobs. After the separation part, another convolutional layer (marked with purple) expands the intermediate data to masks whose size will be significantly increased (indicated by a thicker line in Fig. 2). The last convolutional layer (marked with green) decodes the data into the time-domain and also causes an increase in the length of the data.

Conv-TasNet is a valuable candidate to demonstrate how to accommodate a DNN into an in-network scheme. The reasons are as follows. First, Conv-TasNet utilizes lightweight 1-D convolutional blocks to separate the observed signals. Such a lightweight design reduces the overall computational complexity with guaranteed separation accuracy that makes it suitable for deployment in networks. Deriving an in-network solution for it will also be instrumental for other similar BSS problems. Second, we will see that splitting its CNN will face all challenges we mentioned before. Therefore, this exemplifies how the three proposed principles shall be exercised in practice.

C. Splitting Conv-TasNet into DP

Refer to the three principles introduced in Section III-A, Conv-TasNet is split into ten neural blocks, as shown in Fig. 2.

Following Principle-1, with homogeneous UPFs, we initially split Conv-TasNet into eight even neural blocks, each of which occupies approximately 12.649% out of 0.663 millions of model parameters defining the entire CNN. Specifically,

the first neural block contains the encoding part convolutional layer and a subset of separation part convolution layers; the next six neural blocks correspond to the second to seventh evenly split convolutional layers of the separation part; the eighth neural block contains the rest of the separation part convolutional layers (including mask) and the decoding part. Note that the separation part occupies almost 98.764% parameters while all the other parts share the rest 1.236%.

According to Principle-2, furthermore, the last neural block (i.e., the rest of the separation part and the mask plus decoding part) enlarges output data size, which leads to traffic explosion to stress network bandwidth to the server node. Therefore, the decoding part is taken out as a new neural block and merged to the server node. This hides the explosion inside the server node thus avoiding large volume temporal data flooding the network link.

Observing the computing logic of the encoding part, its output is needed by both the separation part and the last decoding part. To prevent the last convolutional layer from waiting for temporal output, with Principle-3 we split the convolutional layer of the decoding part as a separate neural block, so that its output data can be directly sent to the last in parallel.

Ultimately, from the initial eight neural blocks, with considering Principle-2 and Principle-3, the total number of split neural blocks becomes ten. For illustration, Fig. 2 shows a mapping with its final deployment on DP consisting of UPFs and the server node, given that every UPF can accommodate maximum of two neural blocks, i.e., δ -type is 2 as how we define later.

V. EVALUATION

A. Experimental setups

We emulated the proposed enhancements with a network emulator–ComNetsEmu developed in [14]. The reason to choose ComNetsEmu is because of its full capability of supporting both NFV and SDN. Specifically, we used ComNetsEmu to implement the extended DP described in Section III-A and accommodated the split Conv-TasNet solution introduced in Section IV-C. The virtualized network node created by ComNetsEmu is equivalent to a UPF with a split DNN component. Hence, a series of virtualized nodes form the DP running the data separation service. Additionally, the SDN controller mimics the role of extended MP and CP introduced in Section III-B.

Data was transmitted with User Datagram Protocol (UDP) and the bandwidth between UPFs was 1 *Gbps* with propagation delay 10 *ms*. These are normal conditions in an average network system. Since we mainly focused on the split of NN models, we assumed that possible transmission failures were handled by lower-layer protocols. All emulations were done on a COTS server with an Intel(R) Xeon(R) Gold 6148 CPU 2.40GHz and 4GB RAM using Ubuntu 18.04.4 LTS.

1) Scenarios: We evaluated under a linear topology with two different DP path lengths: three and five hops (i.e., namely 3H-N and 5H-N), respectively. This is in the typical range of the UPF numbers in an operator's network from a UE to

TABLE I: Distributions of ten neural block# on network elements within two network path lengths. The first neural block always occupies one UPF and the last neural block is always on server node.

δ- Type	Max. Neural Block♯ per UPF	Neural Block‡ on Server (UPF‡ = 3)	Neural Block# on Server (UPF# = 5)
0	NULL	10	10
1	1	7	5
2	2	5	1
3	3	3	1
4	4	1	1

data networks. We considered five types of UPFs, numbered with an integer value δ from $0 \to 4$. Each δ -type represents a UPF with the capacity to accommodate maximally δ numbers of Conv-TasNet's neural blocks onboard. In particular, the scenario of 0-type UPFs was used as the baseline system, since δ equals zero means that the network has no in-network DL enhancement, in this case, it is equivalent to the original Conv-TasNet scheme in [3]. Table I gives the detailed network topology configurations consisting of different δ -type UPFs and a server end. In addition to comparing with Conv-TasNet without in-network DL capability, we also selected a recent non-DL-based solution – progressive ICA (pICA) [4] for comparison.

For each configuration in Table I, we performed 50 tests i.e., 50 randomly selected datasets will be processed with our implementation in the ComNetsEmu emulator.

2) Metrics: The first metric is residual time, which tells the residual time taken by the last node (i.e. server node) to finalize the entire data separation jobs. The smaller the residual time, the more jobs were done by the intermediate network nodes. Therefore, it measures the acceleration speed to the DL service application service.

The second metric is *Source-to-Distortion Ratio (SDR)*, which is used to evaluate the separation accuracy of Conv-TasNet service. The SDR definition is the most widely used metric nowadays because different types of errors, i.e., interference, noise, and artifacts errors, are comprehensively considered. This metric examines whether the accuracy of neural networks has been affected by in-network computing.

3) Dataset: We picked a public open dataset from [15], called Malfunctioning Industrial Machine Investigation and Inspection (MIMII). The main reasons for choosing the MIMII dataset are as follows. First, it is a well-known dataset that is widely referenced in research and engineering for acoustic machine anomaly detection. In addition, it exactly reflects the theme of this work, i.e., processing the most relevant acoustic data of factory machines from industry rather than random acoustic data such as music or daily life data.

This dataset has collected 26092 normal and anomalous operating sound data of four types of machines. 2-second-long audio of each segment is used, which is single-channel with a sample rate of 16 kHz. The size of one data source is 32k.

B. Residual computing time and separation quality

Fig. 3 shows the residual time on the server node when using the DL-based Conv-TasNet (with and without the proposed DP

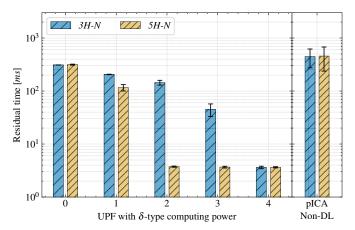


Fig. 3: Residual time of the DL-based Conv-TasNet and the non-DL-based pICA on DP.

enhancement) and pICA, which is an ICA algorithm but not based on DL, under the two DP lengths with different δ -type UPFs.

The first observation is that no matter if using DP enhancement, Conv-TasNet showed smaller residual time than pICA has, e.g., $310\ ms$ of 0-type UPF v.s. $447\ ms$ of pICA in 3H-N. This is because of the nature of the Conv-TasNet method, where Conv-TasNet needed less input data thus less overall workloads. This justifies that Conv-TasNet is representative to the benefits of DL-based methods.

Secondly, boosted with the proposed DP enhancement, when the computing resources gradually increased, the residual time on the server node could be further reduced. Specifically, given the same DP path length, the more powerful the UPFs were used, the smaller the residual time would be spent on the server node. The residual time was reduced by 98.83% when the δ -type went from zero to four in the 3H-N scenario. Similarly, given the same δ -type UPFs, the longer the DP path length, the smaller the residual time would be spent on the server node. For instance, by increasing the path length of 2-type UPFs from three to five, the residual time fell from 144.34~ms to 3.74~ms.

Moreover, it showed an upper bound of the acceleration, influenced by both the computing resources of the UPF and the offloaded neural blocks. Specifically, in 5H-N case, the residual time reduced to $3\ ms$ and did not change anymore since UPF type was two and onward. This is because according to the Conv-TasNet splitting in Section IV-C, maximally only nine intermediate nodes were needed to accommodate all split neural blocks even if the UPF δ -type equals one. Hence, adding more intermediate UPFs will not further improve the acceleration (i.e., reducing residual time on the server node).

Last but not least, Fig. 4 shows the achievable separation quality, SDR, with the proposed in-network scheme within the two different DP path lengths. All SDRs had no noticeable loss (about 71 dB) compared with the original centralized ConvTasNet (i.e., the UPF with δ -type is zero). This is because although we split the whole CNN into several neural blocks, its structure across all UPFs was not modified. This suggests that running the DL inference jobs with the DP enhancement

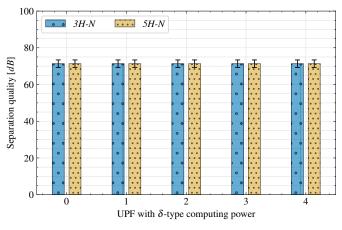


Fig. 4: The separation quality of DL-based ConvTasNet on DP.

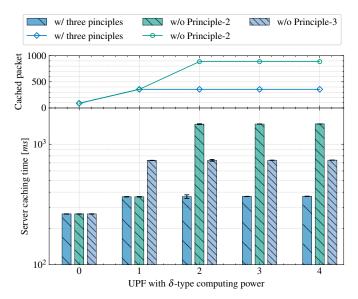


Fig. 5: The caching time and the number of cached packets on the server in 5H-N.

can be a promising potential scheme.

C. Traffic explosion avoidance

Between two adjacent UPFs, since the neural blocks on a UPF may increase the size of output data, this may cause traffic explosion on the link to the next UPF. The traffic explosion can be mitigated by carefully splitting the CNN at the layers whose temporal data size is smaller, i.e., Principle-2 avoiding inter-UPF traffic explosion introduced in Section III-A.

As shown in Fig. 5, without following Principle-2, the number of packets cached by the server grew from 356 to 886, and the caching time increased four times from $366\ ms$ to $1472\ ms$ when δ was bigger than one. As we explained, this is because the mask part (the purple block in Fig. 2) is a splitting point that will temporally increase the output data size. Hence, we merged this layer to the server end following Principle-2, this avoided sending large data traffic to the network link. As we can see, the caching time remained $366\ ms$, which was slightly higher than $263\ ms$ of 0-type UPF only. This

again confirms the influence of the splitting points to the traffic generated in the network.

D. Processing and forwarding parallelization

We also measured the caching time at the server waiting for caching required processing data, presented in Fig. 5. This caching time can be improved by Principle-3 in Section III-A.

Fig. 5 provides a comparison on processing and forwarding with and without Principle-3 in 5H-N scenario. With the applied parallelization scheme, the server started receiving the encoding data at the same time as the UPF, therefore, the idle time was only about $103\ ms$, a 78.09% reduction. In contrast, without parallelization, the caching time of the server increaseed from $263\ ms$ to $733\ ms$, i.e., the server was idle approximately $470\ ms$. This is because the encoding part and the first separator belong to the same neural block, which causes UPF to forward the intermediate data to the server only after it completes all operations. This confirms the necessity of such a parallelization consideration and the result confirms its effectiveness to improve the efficiency at the server end.

VI. CONCLUSION

This paper presents a DP enhancement with accommodating an application-specific in-network deep learning. In particular, the focus is on how to split a trained DNN model so that it can fit into UPFs along a forwarding path. Taking a specific use case - Blind Source Separation - as an example, we demonstrated how a CNN used in an existing work shall be split with our proposed principles. Furthermore, we implemented the suggested scheme with a full-stack emulator - Communication Networks Emulator (ComNetsEmu) and showed that the proposed enhancement indeed yields noticeable caching accelerations and reduces the workload left to the server end. Since the structure of the CNN is untouched, we believe that the suggested strategy/principles shall be applicable to other DL application services based on DNN. As an initial trial, our work also reveals further challenges that require deeper investigations from the whole community when considering splitting a CNN onto in-network elements, to support AI application in future 6G.

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REFERENCES

[1] C. Lao, Y. Le, K. Mahajan, Y. Chen, W. Wu, A. Akella, and M. Swift, "ATP: In-network aggregation for multi-tenant learning," in 18th USENIX Symposium on Networked Systems Design and Implementation (NSDI 21). USENIX Association, Apr. 2021, pp. 741–761.

- [2] H. T. Dang, P. Bressana, H. Wang, K. S. Lee, N. Zilberman, H. Weatherspoon, M. Canini, F. Pedone, and R. Soulé, "P4xos: Consensus as a network service," *IEEE/ACM Transactions on Networking*, vol. 28, no. 4, pp. 1726–1738, 2020.
- [3] Y. Luo and N. Mesgarani, "Conv-tasnet: Surpassing ideal time–frequency magnitude masking for speech separation," *IEEE/ACM transactions on audio, speech, and language processing*, vol. 27, no. 8, pp. 1256–1266, 2019.
- [4] H. Wu, Y. Shen, X. Xiao, G. T. Nguyen, A. Hecker, and F. H. P. Fitzek, "Accelerating industrial iot acoustic data separation with in-network computing," *IEEE Internet of Things Journal*, pp. 1–16, 2022.
- [5] H. Wu, Z. Xiang, G. T. Nguyen, Y. Shen, and F. H. Fitzek, "Computing meets network: Coin-aware offloading for data-intensive blind source separation," *IEEE Network*, vol. 35, no. 5, pp. 21–27, 2021.
- [6] H. Xu, C.-Y. Ho, A. M. Abdelmoniem, A. Dutta, E. H. Bergou, K. Karatsenidis, M. Canini, and P. Kalnis, "Grace: A compressed communication framework for distributed machine learning," in 2021 IEEE 41st International Conference on Distributed Computing Systems (ICDCS), 2021, pp. 561–572.
- [7] S. Trindade, L. F. Bittencourt, and N. L. S. da Fonseca, "Management of resource at the network edge for federated learning," *CoRR*, vol. abs/2107.03428, 2021. [Online]. Available: https://arxiv.org/abs/2107. 03428
- [8] F. Liang, W. Yu, X. Liu, D. Griffith, and N. Golmie, "Toward edge-based deep learning in industrial internet of things," *IEEE Internet of Things Journal*, vol. 7, no. 5, pp. 4329–4341, 2020.
- [9] B. M. Xavier, R. S. Guimarães, G. Comarela, and M. Martinello, "Programmable switches for in-networking classification," in *IEEE INFOCOM 2021 - IEEE Conference on Computer Communications*, 2021, pp. 1–10.
- [10] M. Saquetti, R. Canofre, A. F. Lorenzon, F. D. Rossi, J. R. Azambuja, W. Cordeiro, and M. C. Luizelli, "Toward in-network intelligence: Running distributed artificial neural networks in the data plane," *IEEE Communications Letters*, vol. 25, no. 11, pp. 3551–3555, 2021.
- [11] C. Zhang, P. Patras, and H. Haddadi, "Deep learning in mobile and wireless networking: A survey," *IEEE Communications surveys & tutorials*, vol. 21, no. 3, pp. 2224–2287, 2019.
- [12] H. Wu, J. He, M. Tömösközi, Z. Xiang, and F. H. Fitzek, "In-network processing for low-latency industrial anomaly detection in softwarized networks," in 2021 IEEE Global Communications Conference (GLOBE-COM), 2021, pp. 01–07.
- [13] P. Comon and C. Jutten, Handbook of Blind Source Separation: Independent component analysis and applications. Academic press, 2010.
- [14] Z. Xiang, S. Pandi, J. Cabrera, F. Granelli, P. Seeling, and F. H. P. Fitzek, "An open source testbed for virtualized communication networks," *IEEE Communications Magazine*, vol. 59, no. 2, pp. 77–83, 2021.
- [15] H. Purohit, R. Tanabe, T. Ichige, T. Endo, Y. Nikaido, K. Suefusa, and Y. Kawaguchi, "MIMII Dataset: Sound dataset for malfunctioning industrial machine investigation and inspection," in *Proceedings of the Detection and Classification of Acoustic Scenes and Events* 2019 Workshop (DCASE2019), 11 2019, pp. 209–213.

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