Intelligence Slicing: A Unified Framework to Integrate Artificial Intelligence into 5G Networks

Wei Jiang*†, Simon Duque Anton*, and Hans Dieter Schotten†*
*Intelligent Networking Research Group, German Research Center for Artificial Intelligence (DFKI)
Trippstadter street 122, Kaiserslautern, 67663 Germany
†Institute for Wireless Communication and Navigation, University of Kaiserslautern
Building 11, Paul-Ehrlich street, Kaiserslautern, 67663 Germany

***Abstract*—The fifth-generation and beyond mobile networks should support extremely high and diversified requirements from a wide variety of emerging applications. It is envisioned that more advanced radio transmission, resource allocation, and networking techniques are required to be developed. Fulfilling these tasks is challenging since network infrastructure becomes increasingly complicated and heterogeneous. One promising solution is to leverage the great potential of Artificial Intelligence (AI) technology, which has been explored to provide solutions ranging from channel prediction to autonomous network management, as well as network security. As of today, however, the state of the art of integrating AI into wireless networks is mainly limited to use a dedicated AI algorithm to tackle a specific problem. A unified framework that can make full use of AI capability to solve a wide variety of network problems is still an open issue. Hence, this paper will present the concept of intelligence slicing where an AI module is instantiated and deployed on demand. Intelligence slices are applied to conduct different intelligent tasks with the flexibility of accommodating arbitrary AI algorithms. Two example slices, i.e., neural network based channel prediction and anomaly detection based industrial network security, are illustrated to demonstrate this framework.**

I. Introduction

The charm of the fifth-generation (5G) wireless systems is its flexibility to support a wide variety of new applications and services, such as Internet of Things, Tactile Internet [1], automated driving, virtual and augmented reality, e-Health, and smart factory. To satisfy their highly diversified requirements, the 5G network and its upcoming evolution should support extremely high data rate, ultra reliability, low latency, excessive energy efficiency, strict security and privacy protection, ubiquitous coverage, and massive connection. It can be envisioned that more advanced signal transmission techniques, more efficient spectral, radio, and computing resources utilization, more agile physical and virtual network function orchestration, more autonomous network slicing management, and more finer analysis methodology for network big data and user behaviour, are needed to be developed. Fulfilling these tasks is challenging since the network infrastructure becomes increasingly complicated, heterogeneous, large-scale, and ubiquitous, while the emergence of new applications increasingly speeds up.

One potential solution is to leverage Artificial Intelligence (AI), which provides data-driven approaches that can be applied to solve complex and previously intractable problems. In March 2016, when Google AlphaGo [2] achieved an overwhelming victory versus human champion in the game of Go, the passion of exploring AI in all scientific and technological aspects has been sparked [3]. Actually, the wireless research community started to apply AI algorithms to solve communication problems long ago. It has been explored to provide a wide variety of technical solutions, e.g., recurrent neural network (RNN) for Multi-Input Multi-Output (MIMO) fading channel prediction [4], deep learning based resource allocation [5], supervised learning for network security [6], reinforcement learning in cognitive radio [7], and intelligent network management [8]. However, the state of the art of applying AI technology into wireless networks is mainly limited to use a dedicated AI algorithm to tackle a specific problem like [4]-[8]. Although the SELFNET project [9] has proposed an intelligent framework over software-defined virtualized infrastructure, it merely focused on applying AI dedicated for network management. A framework that can take advantage of AI technology to solve network problems in a unified manner is still an open issue.

To fill the gap, this paper will present the design of a unified framework that has generality and scalability to integrate AI to conduct intelligent tasks for all network aspects, ranging from radio channels to signal processing, from resource allocation to network slicing orchestration, from local control to end-to-end optimization. The concept of intelligence slicing, with the flexibility to instantiate, deploy, scale, reconfigure, and transfer AI functional modules on demand, will be presented. An intelligence slice can be deployed in an arbitrary network entity to well solve a problem by means of selecting the best algorithm specifically optimized for this problem. Two example slices, i.e., RNN-based MIMO channel prediction to improve the accuracy of transmit antenna selection and security anomaly detection in industrial networks, are illustrated to demonstrate this framework.

This paper is organized as follows: Section II presents the AI framework and the concept of intelligence slicing, followed

*This work was supported by the German Federal Ministry of Education and Research (BMBF) in part under the *TACNET4.0* project (*KIS15GTI007*) and in part under the *IUNO Insec* project (*16KIS0932*). The authors alone are responsible for the content of the paper.

ISBN 978-3-903176-18-8 © 2019 IFIP

by its life-cycle management in Section III. Section IV depicts two example slices, and conclusions are made in Section V.

II. The unified AI Framework

This section introduces the AI framework over software-defined virtualized 5G infrastructure, followed by the concept of intelligence slicing that provides the flexibility of instantiating and deploying AI functional modules into the network on demand.

A. The Framework

Software-Defined Networking (SDN) [10] and Network Function Virtualization (NFV) [11] were initially developed as independent networking paradigms by Open Networking Foundation (ONF) and European Telecommunications Standards Institute (ETSI), respectively. But they have shown strong synergy and combining them in one networking architecture may lead to great value. For instance, an SDN controller can be implemented in a software program running on computers as a Virtual Network Function (VNF). The network control and management applications (i.e., SDN APPs), such as security, Mobile Load Balancing (MLB) and Quality-of-Experience (QoE) provisioning for ultra-high-definition video delievery, can be also realized as VNFs. Virtual computing, storage and networking resources under the control of Virtualized Infrastructure Manager (VIM) can be leveraged by SDN to facilitate the flexibility to program the underlying networks. Taking advantage of SDN and NFV, network slicing [12] that allows multiple virtual networks to provide dedicated functionality specific to the service or customer, can be instantiated on the top of a shared physical infrastructure, as shown in Fig.1, where Physical Network Functions (PNFs) are used in order to represent legacy components (non-NFV or non-SDN).

Network programmability is available through Application Programming Interface (API), the intelligent processing, control, and management functions provided by the AI framework can be regarded as external APPs on the top of software-defined virtualized infrastructure. As shown in Fig.1, the AI framework mainly consists of the following three different functional components:

Intelligence slices are AI functional modules that are deployed in the network to individually or collaboratively accomplish intelligent tasks such as radio scheduling in a MIMO system, MLB, video QoE provisioning, and security. Intelligence slices can be instantiated on demand at different levels to achieve dedicated intelligent tasks with the aid of the most suitable AI algorithm specifically optimized for this task. Although slices are controlled by a centralized entity, as shown in Fig.1, it is only *logically* meaningful. Actually, a slice should be *physically* deployed in a *distributed* manner close to its functional area to make time-sensitive decisions and offload the traffic passing the core network.

The slice manager is in charge of managing intelligence slices on the basis of communicating with the network. Once received a request for a dedicated intelligence task, the manager instantiates an intelligence slice following a unified

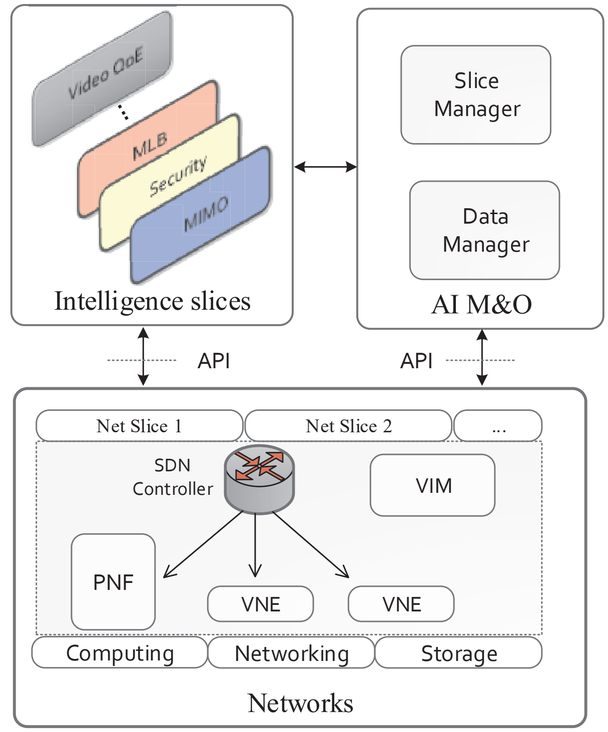

Fig. 1. A unified AI framework based on intelligence slicing over the software-defined virtualized 5G infrastructure.

procedure. After selecting an AI algorithm that is the best for this task and training, testing this algorithm with appropriate data, the slice is deployed in the network part where well suits to perform the task, e.g., at mobile edge. During its operation, its life-cycle management such as reconfiguring, scaling, and destroying, will be conducted by the manager.

The data manager that is responsible for acquiring, modelling, processing, transferring, and storing data in a unified and efficient manner. The data can be from both historically off-line sources, public or proprietary, and real-time online collected from complex, heterogeneous, dynamic, and large-scale networks. It not only provides data sets necessary for training and testing AI algorithms but also delivers monitored data in a timely, securely, and accurately way during the operation of intelligence slices.

B. Intelligence Slicing

The 5G network control and management faces increasingly challenging situation than ever before. Most of the traditional tasks still remain, while some probably become more severe, e.g., the Distributed Denial-of-Service (DDoS) cyber-attack will be more impactive due to the introduction of Internet-of-Thing, where an attacker is able to compromise a large number of machine-type terminals as zombies. In addition, a large number of new tasks will emerge from the water, such as guaranteeing ultra reliability for mission-critical control, low latency for time-sensitive services, radio scheduling in a massive MIMO system operating in millimeter wave bands, orchestrating virtual resources, and managing network slices.

Different tasks have different characteristics and requirements so that finding a universal AI algorithm that can tackle all tasks is impossible. For example, transmit antenna selection in a MIMO system requires a very prompt decision with the aid of a few local data since radio channels vary within milliseconds. The detection of DDoS attacks needs a global view of network, leading to a huge data volume to be processed, while the time for decision is far relaxed than a millisecond. Moreover, due to the dynamicity of 5G infrastructure, the best algorithm for the current situation might be outdated with time goes.

In large-scale and heterogeneous networks, centralized processing all monitored data is inefficient and hard to meet the real-time requirement [13]. Therefore, in this paper, the concept of intelligence slicing is presented to enable a flexible and scalable framework that can instantiate an AI functional module on demand and deploy these modules in a distributed manner, as shown in Fig.2. Following the *divide-and-conquer* strategy, each slice only focuses on a dedicated intelligent task with the aid of the best suitable algorithm specially optimized for this task. For instance, an MIMO slice is deployed in a Base Station (BS) taking advantage of a RNN to predict fading channel so as to intelligently select its transmit antennas, while another slice for network security can be instantiated in the data center of an industrial site to detect anomalous traffic. Different slices operate independently so that each slice has a flexibility to instantiate, deploy, reconfigure, and scale in terms of its respective situation.

III. Life-cycle Management of Slices

Once a slice is instantiated to handle an intelligence task, its life starts. During its operation, for example, the behavioral pattern of the target problem might vary due to the change of underlying infrastructure or environment, leading to the necessity of reconfiguring or scaling. In this section, the life-cycle management of slices will be detailed.

1) Instantiation: Once the slice manager receives a request from the network, a slice or a number of slices are instantiated in the AI framework following a certain predefined procedure. The associated features of the task are analyzed to qualitatively decide a suitable AI technique, for example, among supervised, unsupervised, reinforcement learning, etc. For each learning technique, there is a number of different algorithms, e.g., supervised learning technique can provide solutions based on Decision Tree, Linear Discriminant Analysis, Support Vector Machine, Nearest Neighbor, Neural Network, Deep Learning, etc. The slice manager continues to make a quantitative decision, e.g., by means of calculating achievable performance comparatively for available algorithms. Then, that algorithm achieved the best performance is applied in this slice. Afterwards, the slice is deployed into the network.

2) Reconfiguration: There are two possible reasons for reconfiguring a slice. First, the pattern of the intelligent task is possible to change due to the dynamicity of infrastructure or external environment. For example, a cellular cell close to a shopping center is prone to be congested. Later, a small-cell BS is deployed there and the corresponding congestion vanishes from then on. In addition to the change of a pattern, another motivation for reconfiguring is the emergence of a novel algorithm that can better process a fixed pattern. During the process of reconfiguration, the best algorithm is re-selected with the updated training data set.

3) Scaling: Scaling means the functional coverage of an intelligence slice being enlarged or shrunk, or the processing resources being augmented or partially released since its associated task varies due to the dynamicity of underlying infrastructure or external environment. For example, at the early stage, a cloud-RAN Base-Band Unit (BBU) associates with ten Remote Radio Units (RRUs) with an intelligence slice deployed in this BBU to conduct inter-cell interference coordination and MLB in a centralized manner. When the network becomes denser by deploying several new RRUs, this BBU have to extend to its coverage area with a larger number of RRUs. Accordingly, this slice probably needs more computing resource for increased processing capability.

4) Transferring: The establishment of an intelligence slice is not a trivial work since a learning system needs to be trained into a learned system. For supervised and unsupervised learning, a training dataset is necessary. Data acquisition is sometimes difficult, especially for supervised learning, where data need to be labeled. Reinforcement learning does not need training dataset, but the learning system has to iteratively try all possible actions for each state and observe their outcomes. The learning process is time-consuming and computationally complex. In a large-scale network, if each intelligence slice for the same task is independently trained, it will be a tremendous work. Relying on the transfer learning, a partial model can be trained in the AI framework and distributed to different deployment places where the partial model can be re-trained with local data to satisfy their special requirements and lower the training load.

IV. Proof of Concept

To further shed light on the framework and prove the concept of intelligence slicing, two examples slices, i.e., RNN-based fading channel prediction to improve the accuracy of transmit antenna selection in a MIMO system, and to detect security threats in an industrial network, are illustrated.

A. RNN-based MIMO Channel Prediction

Provided accurate channel state information (CSI) at the transmitter, a closed-loop technique called adaptive transmission system achieves a great performance gain over open-loop schemes. Due to feedback and processing delays, CSI at the transmitter might be outdated before its actual usage, especially in fast fading channels. Outdated CSI has a severe impact on the performance of a wide variety of adaptive wireless techniques, such as precoding in MIMO [14] and Massive MIMO [15], interference alignment [16], transmit antenna selection [17], cooperative relaying [18], coordinated multi-point transmission [19], etc. In the literature, a large number of algorithms and protocols have been proposed to combat outdated CSI. However, these methods either *passively*

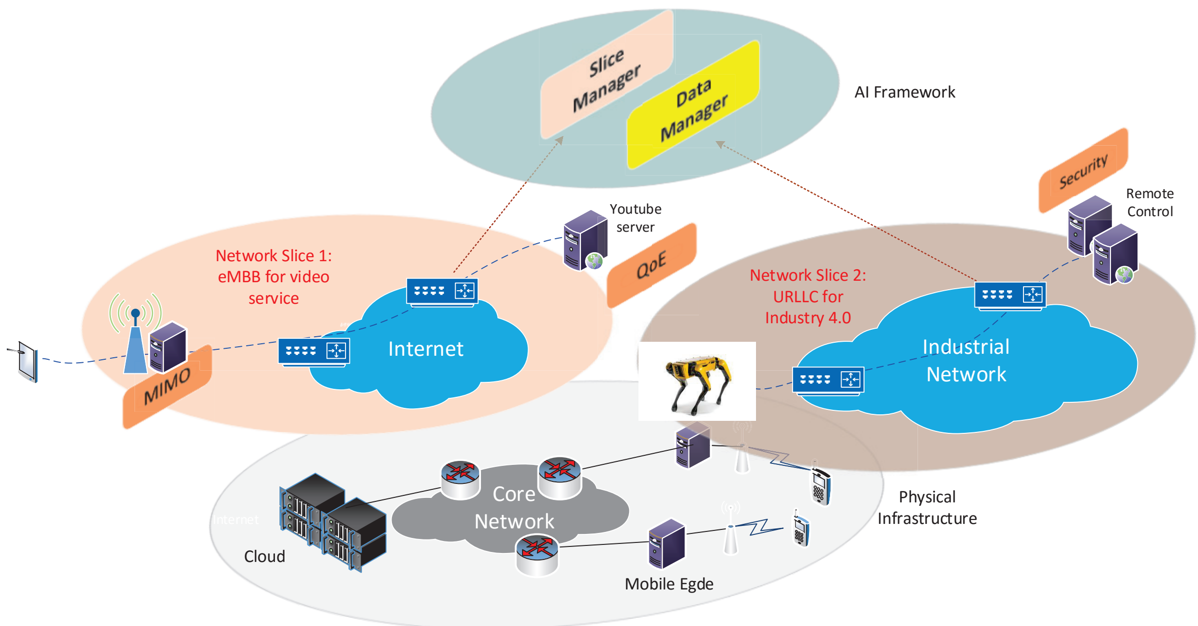

Fig. 2. Illustration of distributed deployment of intelligence slices under the unified management of the AI framework.

compensate for the performance loss with a cost of scarce wireless resources [18] or aim to achieve merely a portion of the full potential under imperfect CSI [20].

A technique referred to as channel prediction that can *actively* forecast future CSI has drawn much attention from researchers due to its potential of effectively and efficiently solving this problem. Therefore, the authors in [21] demonstrated the application of a RNN to build a predictor for the fading channel. RNN [22] is a popular AI technique that has shown a high promise in time-series prediction. Without loss of generality, a multi-antenna wireless system with N_t transmit and N_r receive antennas in a flat fading channel can be modeled as

$$\mathbf{y}(t) = \mathbf{H}(t)\mathbf{x}(t) + \mathbf{z}(t), \tag{1}$$

where $\mathbf{y}(t)$ represents the $N_r\times 1$ received vector at time t, $\mathbf{x}$ is the $N_t\times 1$ transmit symbol vector, $\mathbf{z}$ stands for the vector of additive white Gaussian noise, $\mathbf{H}(t)=[h_{n_r n_t}(t)]_{N_r\times N_t}$ is the instantaneous channel matrix, and $h_{n_r n_t}\in\mathbb{C}^{1\times 1}$ represents complex-valued channel gain between transmit antenna n_t and receive antenna n_r, where $1\leqslant n_r\leqslant N_r$ and $1\leqslant n_t\leqslant N_t$. Due mainly to the feedback delay, the CSI at the time of selecting adaptive parameters may be outdated before its actual usage, namely $\mathbf{H}(t)\neq\mathbf{H}(t+\tau)$, where τ denotes the delay. The outdated CSI imposes a severely negative impact on a wide variety of wireless techniques. The task of channel prediction is to get the predicted CSI $\hat{\mathbf{H}}(t+\tau)$ that is as close as possible to the actual CSI $\mathbf{H}(t+\tau)$.

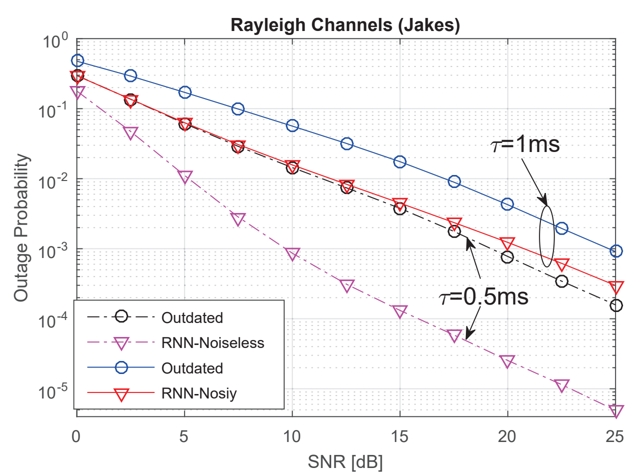

Fig. 3. Outage probabilities as a function of average transmit SNR in a TAS system with the aid of channel prediction.

As shown in Fig.2, an evolved Mobile Brand-Band (eMBB) network slice supporting high-definition video delivery is instantiated on a shared physical infrastructure. Using the mobile edge computing resources, an MIMO intelligence slice is deployed at the BS, which runs a RNN algorithm to conduct fading channel prediction so as to improve the quality of Transmit Antenna Selection (TAS). The performance in terms of outage probability is evaluated through Monte-Carlo simulation in a flat fading channel with an average gain of

0dB, i.e., $h\sim\mathcal{CN}(0,1)$. The symbol rate is set to $f_s{=}10^5\mathrm{Hz}$ to satisfy the flat fading assumption and the maximal Doppler frequency is $f_d{=}100\mathrm{Hz}$ to emulate fast fading environment. The signal transmission is organized in block-wise, with a block size of 50 symbols including N_t antenna-specific pilot symbols inserted at the head of each block. A three-layer RNN is applied to build the predictor and the Levenberg-Marquardt algorithm [23] is used to train the neural network.

To decide the transmit antenna for upcoming block $t{+}D$, the possible selection methods are:

- The *outdated* mode in traditional TAS systems where the outdated CSI $\mathbf{H}(t)$ is applied.
- The *prediction* mode makes a selection decision based on the predicted CSI $\hat{\mathbf{H}}(t{+}D)$ that probably approximates $\mathbf{H}(t{+}D)$.

The performance assessment is first carried out in noiseless MIMO channel with 4 transmit and 1 receive antennas. The RNN predictor is tuned to the a prediction range of $\tau{=}0.5ms$. As illustrated in Fig.3, the TAS system with the aid of the MIMO slice can obtain a remarkable SNR gain of around $10\mathrm{dB}$ over the outdated CSI. In practice, estimated channel gains are impaired by additive noise that cannot be avoided in the process of channel estimation. Under the assumption that the SNR of pilot symbols is $\mathrm{SNR_p}{=}30\mathrm{dB}$, the performance evaluation in noisy channels is also conducted. Further increased the prediction range to $\tau{=}1.0ms$, the performance gain brought by the MIMO slice is more than $4\mathrm{dB}$ in comparison with the outdated mode. Recalling the used fast fading with the Doppler shift of $f_d{=}100\mathrm{Hz}$, this prediction range is meaningful from the practical view in comparison with the length of a radio frame of $10\mathrm{ms}$ in LTE systems for example.

B. Industrial Network Security

Malware is a challenging issue for any domain connected to the network infrastructure. Information leakage, spear phishing, cryptolockers and botnets are the most notorious types of attacks launched against government, businesses, and persons. For about 15 years, not only the Information Technology (IT) assets of organisations has been affected, but the Operation Technology (OT) facility as well. In contrast to IT in the cyber world, OT commonly controls physical devices and machines that interact with the real world, also known as Cyber Physical Systems (CPSs). If an attack against a CPS is successfully carried out, physical entities can be affected, as the infamous *Stuxnet*-attacks [24], suffering from a more severe damage and economic loss than that of attacks within the cyber world.

As one of the pillars of 5G, Ultra-Reliable Low-Latency Communications (URLLC) will open the possibility of interconnecting industrial sites to realize smart manufacturing in the era of Industry 4.0. It can be envisaged that a large number of local industrial networks will be connected to the wide-area 5G network infrastructure. However, legacy communication protocols running on these industrial networks, such as *Profinet*, *Profibus*, and *Modbus* were not designed with network security in mind, e.g., lacking authentication or encryption. This feature enables attackers to act freely, once they have broken the perimeter. In consequence, anomaly detection methods [25] for industrial networks are required that are:

- compatible with legacy systems,
- work without feedback to the process, and
- can autonomously distinguish normal from anomalous behaviour.

As shown in Fig.2, a URLLC network slice dedicated for a local industrial network is instantiated on a shared infrastructure. Using the cloud computing resources at the remote data or control center, a security intelligence slice running machine learning-based anomaly detection algorithms, i.e., *Random Forest* and *Support Vector Machine* (*SVM*), is deployed. As the key performance indicator for anomaly detection, the detection accuracy is evaluated with the data sets for industrial networks, provided by *Lemay and Fernandez* [26]. As illustrated by the accuracy and f1-score for the *SVM* algorithm in Table I, as well as the results of *Random Forest* in Table II, the achieved detection accuracy is quite high. For example, the *SVM* algorithm can achieve the optimal accuracy of 100% in detecting false negatives and postivies in the first two data sets, as well *Random Forest* in the first data set. The third data set is a combined one, consisting of different data sets provided by *Lemay and Fernandez*. It was created to evaluate the impact of different production settings on the detection quality.

TABLE I
Accuracy AND *F1-score* OF *SVM*

Dataset	***Accuracy***	***F1-score***
DS1	1,0	1,0
DS2	1,0	1,0
DS3	0,999 936	0,999 968

TABLE II
Accuracy AND *F1-score* OF *Random Forest*

Dataset	***Accuracy***	***F1-score***
DS1	1,0	1,0
DS2	0,999 701	0,999 851
DS3	0,999 973	0,999 986

V. Conclusions

To leverage the great potential of Artificial Intelligence to solve complex and previously intractable problems in wireless networks, an AI framework was presented in this paper. Instead of applying a dedicated AI algorithm to tackle a specific network problem individually, the framework can instantiate and deploy AI functional modules on demand, following a unified manner. Taking advantage of the concept of intelligence slicing, this framework provides flexibility and scalability to accommodate arbitrary AI algorithms to conduct a wide variety of intelligence tasks in the 5G networks and beyond. Two example slices, i.e., neural network based MIMO channel prediction and security anomaly detection in industrial networks, were illustrated to demonstrate this framework. The results of this paper provided a preliminary exploration of using a unified framework to integrate AI into the wireless networks, which will be deepened and further exploited in the future.

References

[1] TACNET 4.0 project. [Online]. Available: http://www.tacnet40.de

[2] D. Silver *et al.*, "Mastering the game of Go with deep neural networks and tree search," *Nature*, vol. 529, pp. 484–489, Jan. 2016.

[3] W. Jiang, M. Strufe, and H. D. Schotten, "Intelligent network management for 5G systems: The SELFNET approach," in *Proc. IEEE European Conf. on Net. and Commun. (EUCNC)*, Oulu, Finland, Jun. 2017, pp. 109–113.

[4] W. Jiang and H. D. Schotten, "Multi-antenna fading channel prediction empowered by artificial intelligence," in *Proc. IEEE Vehicular Tech. Conf. (VTC)*, Chicago, USA, Aug. 2018.

[5] U. Challita *et al.*, "Proactive resource management for LTE in unlicensed spectrum: A deep learning perspective," vol. 17, no. 7, pp. 4674–4689, Jul. 2018.

[6] K. Hamedani *et al.*, "Reservoir computing meets smart grids: Attack detection using delayed feedback networks," *IEEE Trans. Ind. Informat.*, vol. 14, no. 2, pp. 734–743, Feb. 2018.

[7] A. He *et al.*, "A survey of artificial intelligence for cognitive radios," *IEEE Trans. Veh. Technol.*, vol. 59, no. 4, pp. 1578–1592, May 2010.

[8] W. Jiang, M. Strufe, and H. D. Schotten, "Experimental results for artificial intelligence-based self-organized 5G networks," in *Proc. IEEE Intl. Symp. on Personal, Indoor and Mobile Radio Commun. (PIMRC)*, Montreal, QC, Canada, Oct. 2017, pp. 1–6.

[9] EU H2020 5G-PPP SELFNET project. [Online]. Available: https://selfnet-5g.eu/

[10] B. A. A. Nunes *et al.*, "A survey of software-defined networking: Past, present, and future of programmable networks," *IEEE Commun. Surveys*, vol. 16, no. 3, pp. 1617–1634, 2014.

[11] R. Mijumbi *et al.*, "Network function virtualization: State-of-the-art and research challenges," *IEEE Commun. Surveys*, vol. 18, no. 1, pp. 236–262, 2016.

[12] X. Zhou *et al.*, "Network slicing as a service: enabling enterprises' own software-defined cellular networks," *IEEE Commun. Mag.*, vol. 54, no. 7, pp. 146–153, Jul. 2016.

[13] W. Jiang, M. Strufe, and H. D. Schotten, "A SON decision-making framework for intelligent management in 5G mobile networks," in *Proc. 3rd IEEE Intl. Conf. on Compu. and Commun. (ICCC)*, Chengdu, China, Dec. 2017.

[14] J. Zheng and B. D. Rao, "Capacity analysis of MIMO systems using limited feedback transmit precoding schemes," *IEEE Trans. Signal Process.*, vol. 56, pp. 2886–2901, 2008.

[15] K. T. Truong and R. W. Heath, "Effects of channel aging in Massive MIMO systems," *Journal of Commun. and Net.*, vol. 15, no. 4, pp. 338–351, Sep. 2013.

[16] P. Aquilina and T. Ratnarajah, "Performance analysis of IA techniques in the MIMO IBC with imperfect CSI," *IEEE Trans. Commun.*, vol. 63, pp. 1259–1270, 2015.

[17] X. Yu *et al.*, "Unified performance analysis of transmit antenna selection with OSTBC and imperfect CSI over Nakagami-m fading channels," *IEEE Trans. Veh. Technol.*, vol. 67, pp. 494–508, 2017.

[18] W. Jiang *et al.*, "A robust opportunistic relaying strategy for co-operative wireless communications," *IEEE Trans. Wireless Commun.*, vol. 15, no. 4, pp. 2642–2655, Apr. 2016.

[19] L. Su *et al.*, "The value of channel prediction in CoMP systems with large backhaul latency," *IEEE Trans. Commun.*, vol. 61, no. 11, pp. 4577–4590, Nov. 2013.

[20] D. J. Love *et al.*, "An overview of limited feedback in wireless communication systems," *IEEE J. Sel. Areas Commun.*, vol. 26, pp. 1341–1365, 2008.

[21] W. Jiang and H. D. Schotten, "Neural network-based channel prediction and its performance in multi-antenna systems," in *Proc. IEEE Vehicular Tech. Conf. (VTC)*, Chicago, USA, Aug. 2018.

[22] J. Connor *et al.*, "Recurrent neural networks and robust time series prediction," *IEEE Trans. Neural Netw.*, vol. 5, no. 2, pp. 240–254, Mar. 1994.

[23] X. Fu *et al.*, "Training recurrent neural networks with the Levenberg Marquardt algorithm for optimal control of a grid-connected converter," *IEEE Trans. Neural Netw.*, vol. 26, no. 9, pp. 1900–1912, Sep. 2015.

[24] R. Langner, "To kill a centrifuge," The Langner Group, Tech. Rep., November 2013.

[25] S. Duque Anton, S. Kanoor, D. Fraunholz, and H. D. Schotten, "Evaluation of machine learning-based anomaly detection algorithms on an industrial modbus/tcp data set," in *Proceedings of the 13th International Conference on Availability, Reliability and Security (ARES)*. ACM, 2018.

[26] A. Lemay and J. M. Fernandez, "Providing SCADA network data sets for intrusion detection research," in *9th Workshop on Cyber Security Experimentation and Test (CSET 16)*, Austin, TX, 2016.