ERCIM "ALAIN BENSOUSSAN"
FELLOWSHIP PROGRAMME

Scientific Report

First name / Family name	Massa Ndong
Nationality	Senegal
Name of the *Host Organisation*	Fraunhofer IIS
First Name / family name of the *Scientific Coordinator*	Florian Leschka
Period of the fellowship	01/12/2020 to 30/11/2021

I – SCIENTIFIC ACTIVITY DURING YOUR FELLOWSHIP

- Literature review

A) Radio environment map (REM) for dynamic spectrum sharing

At selected geographical locations, transceiver power can be measured and stored in a database. The same database can be used to store the air interface traffic demand of wireless networks users. Such data storage make the power and traffic maps which can be used to optimize wireless links throughput, reduce outage and improve the efficiency of dynamic spectrum access. The database is called REM. It enables that a user be assigned which frequency block to use for traffic for the next time slot, at what data rate, and in what waveform.

We consider dynamic spectrum sharing between a terrestrial network (TN) and a Non-Terrestrial Network (NTN). The NTN channel propagation is modeled as a line-of-sight and shadowing propagation model. The TN network is a non-line-of sight with small scale fading. The unknown power allocation at some geographical locations are predicted using the REM built by the Kriging interpolation method. The REM provides the power and traffic maps available at any transceiver in the NTN and TN integration of interest for the optimization of the overall network throughput.

B) Terrestrial and non-terrestrial networks integration via deep reinforcement learning

The recent proliferation of low-orbit satellite is an opportunity to enhance 5G-NR users spectrum access. In addition to the ground Base station (gNB), non-terrestrial network base stations (NTN-gNBs) can be used to switch from terrestrial networks (TN) to NTN access [1]. Dynamic spectrum sharing is a tool to improve the throughput of an integrated terrestrial-NTN (T-NTN) system. NTN channel modeling can be found in [2]. The Round Trip Delay (RTD) to be considered for the signal to travel from the TN-NTN terminal (i.e. terminal on the ground) to the NTN-gNB and back (or vice versa) is typically equal to 270.73 ms [3] for regenerative payload-based satellite. A maximization of the aggregated throughput of the TN-NTN terminals is proposed in [1]. Knowledge of the channel state information is required.

Communications between two faraway ground terminals (or cluster of ground terminals) can be enhanced through NTNs instantiated by a duo of low orbit satellite and a mobile high-altitude platform (HAP). The duo is used as a relaying system between two ground terminals to maximize the end-to-end data rate of the link (Source terminal – duo – Destination terminal) [9]. The information is transmitted from the source to the destination via the low orbit satellite node, then via the HAP node. The considered system model consists of a model-free deep reinforcement learning (DRL) framework where the environment is the relaying system and the agent is a DQN. The agent input are the state and reward from the environment. The maximization is solved via DQN because many the state-action space is large and many states may be seldom visited. Such seldom visits incur slow or no convergence of the policy iteration with the matrix of transition probabilities in the Markov chain model. The optimization takes into the dynamic selection of the low orbit satellite in the constellation to pair with the mobile HAP.

C) Dynamic spectrum sharing

License-assisted access(LAA) is a spectrum sharing method allowing a licenced operator to access an unlicensed spectrum. Such access improves the licensed operator network capacity when spectrum is available in the unlicensed spectrum. LAA-LTE is an illustration of such access where an LTE network operator dynamically accesses the WiFi spectrum when the later is unsatured.

WiFi systems use CSMA/CA to access the channel. This incurs long waiting periods specially when there is collision and overheads. The LAA-LTE system will suffer from such condition if it uses CSMA/CA to access the WiFi spectrum. An alternative is to use duty cycles to enable (coordinated or planned) periodical accesses to the WiFi spectrum by the LAA-LTE system. Such access is contrained by the demand of the WiFi users. The LAA-LTE system uses DRL to learn both the WiFi traffic demands and the WiFi traffic model by continuously observing the WiFi activities [5]. The advantage of using DRL is to discard any signaling exchange between the LAA-LTE and the WiFi system.

- Complex-valued neural networks code implementation in python

Complex-valued neural networks (CVNNs) have been introduced as early as 1991 (Haykin) with the development of a backpropagation algorithm where the input and

weights are complex-valued and applied it to radar signal processing and communications problems.
CVNN has been proven to achieve a better accuracy for particular structures of complex-valued data [8]. Treating complex baseband signals as 2-channel real-valued data and using Euclidean metric discards the inherent geometry of the complex-valued data [9].
CVNNs parameters (weights) are complex-valued. Thus, complex-valued activation functions and an adapted learning algorithm is required. This requirement can be satisfied by using Wirtinger calculus to define complex activations with real-valued partial derivatives.
The RadioML dataset is a 2-channel real-valued data generated to represent radio frequency modulations. Each input data point represents a complex number in a vector form where one value is the real part and the other is the imaginary part. The dataset are generated using wireless communications simulation and/or test environment. Several versions of the dataset are available online[9].
I attended the ERCIM poster session where I presented my preliminary results on deep convolutional neural networks for complex-valued input.

- Proposal of a Deep reinforcement learning framework

Dynamic spectrum sharing endeavors to enhance the efficiency of spectrum usage by exploiting the degrees of freedom available in the considered networks. Several spectrum sharing schemes have been investigated in the research and development of wireless communications systems. e.g. carrier aggregation (CA), channel bonding (CB), licensed assisted access (LAA), licensed shared access (LSA) and spectrum access system(SAS). CA and CB aggregate contiguous and/or non-contiguous, and adjacent bands respectively. LAA-LTE allows the aggregation of LTE and WiFi spectra. LSA and SAS access licensed spectrum opportunistically [6] based on prior information provided by a centralized database.
Deep reinforcement learning (DRL) is a combination of deep learning and reinforcement learning. DRL has been proposed to enhance spectrum usage efficiency in a variety of wireless networks: cellular networks with 5G NR and WiFi [7], integration of terrestrial and non-terrestrial network [6], etc.

II – PUBLICATION(S) DURING YOUR FELLOWSHIP

I did not have any publications with my host during this fellowship.
I attended the ERCIM poster session where I presented my preliminary results on deep convolutional neural networks for complex-valued input.

III – ATTENDED SEMINARS, WORKHOPS, CONFERENCES

- Reinforcement learning
  The seminar was hosted by Dr. Georgios Kontes from Fraunhofer.
  His presentation included a theoretical introduction to reinforcement learning with Markov decision process (MDP) and some advanced algorithms. During the seminar, we learn to run some codes on Notebooks. Some useful websites to further address the participants' specific projects were provided.
  I attended the seminar to gain some insights on how to design a deep reinforcement learning algorithm for wireless communications.

IV – RESEARCH EXCHANGE PROGRAMME (REP)

I did not do the research exchange programme.

References

[1] F. Rinaldi, S. Pizzi, A. Molinaro, A. Iera and G. Araniti, "Cooperative Resource Allocation in Integrated Terrestrial/Non-Terrestrial 5G and Beyond Networks," *GLOBECOM 2020 - 2020 IEEE Global Communications Conference*, Taipei, Taiwan, 2020, pp. 1-6

[2] F. P. Fontán, M. Vazquez-Castro, C. E. Cabado, J. P. Garcia and E. Kubista, "Statistical modeling of the LMS channel", *IEEE Transactions on Vehicular Technology*, vol. 50, no. 6, pp. 1549-1567, Nov. 2001.

[3] Solutions for NR to support non-terrestrial networks (NTN), Dec. 2019, [online] Available: https://www.3gpp.org/.

[4] J. -H. Lee, J. Park, M. Bennis and Y. -C. Ko, "Integrating LEO Satellite and UAV Relaying via Reinforcement Learning for Non-Terrestrial Networks," *2020 IEEE Global Communications Conference*, Taipei, Taiwan, 2020, pp. 1-6.

[5] J. Tan, L. Zhang, Y. -C. Liang and D. Niyato, "Deep Reinforcement Learning for the Coexistence of LAA-LTE and WiFi Systems," *ICC 2019 - 2019 IEEE International Conference on Communications (ICC)*, 2019, pp. 1-6.

[6]S. J. D, "Proof-of-concept system for opportunistic spectrum access in multi-user decentralized networks", EAI endorsed transactions on Cognitive communications, 2016.

[7] U. Challita and D. Sandberg, "Deep Reinforcement Learning for Dynamic Spectrum Sharing of LTE and NR", To appear in the IEEE International Conference on Communications (ICC'21), https://arxiv.org/abs/2102.11176

[8]J. A. Barrachina, C. Ren, C. Morisseau, G. Vieillard, J. P. Ovarlez, "Complex-Valued vs. Real-Valued Neural Networks for Classification Perspectives: An Example on Non-Circular Data," 2019,

[9] T. J. O'Shea and N. West, "Radio machine learning dataset generation with GNU radio," in *Proc. GNU Radio Conf.*, 2016, vol. 1, no. 1.