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On the design of a native Zero-touch 6G architecture

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***Abstract*—The complexity of envisioned 6G telecommunication networks requires an intrinsically intelligent architecture designed to autonomously adapt to dynamics with end-to-end zero-touch service automation operations. Motivated by this vision, this paper tries to formulate concepts and solution aspects towards designing a native Zero-touch 6G architecture. Our discussion concentrates around three main pillars, i.e. (i) introducing Machine Learning (ML) models in the core design of the 6G architecture as native functions rather than add-on model solutions; (ii) distributing 6G functionality to different components up to the extreme edge; to (iii) leverage technology leaps enabling, e.g., the use of multi-access technologies and peer-to-peer communications besides the standard cellular connectivity and other centralised functionality.**

***Index Terms*—6G, Zero-touch network Service Management, Closed-Control-Loop, Machine Learning**

I. Introduction

The complexity of real-world communications requires modern network architectures to autonomously adapt and modify their behaviour at runtime to deal with demands of high traffic volume, massive numbers of connected devices with different service requirements, and improved quality of user experience. It is expected, in the coming decade, more than a billion connected devices, including vehicles, robots and in addition to humans will generate zettabytes of data and information. The 5GPPP report [1] suggests that Artificial Intelligence (AI) and ML will play a central role in the 6G ecosystem to exploit and process such amount of generated data. The key features of 6G would include intelligence as a central function to the control, management, programmability and communication [1]. One important operational aspect of the 6G vision is the end-to-end (E2E) system automation for which it is necessary to have ML/AI as an integrated part of the ecosystem [2], [3]. Additionally, the 6G is believed to be rather far more agile and flexible compared to the existing systems with intelligence distributed up-to edge of the future networks [2].

In the context of agility and automation, Zero-touch network and Service Management (ZSM) is expected to play a key role. ZSM is defined by "self-*" features without traditional administrator-like human intervention: self-configuration, self-monitoring, self-healing, and self-optimisation. ZSM focuses on self-management for service automation, i.e., increasing efficiency by automating manual tasks such as those related to network Management and Orchestration (MANO), service workflows, and processes. The concept and fundamental terminology were initially coined by ETSI's homonymous ZSM industry group specification in [4].

The ZSM architecture fostered by ETSI GS ZSM [4], [5], intends to support fully automated network and service management in multi-domain environments. However, we argue and discuss there is no clear framework or standard to interconnect the different components required for ZSM at runtime seamlessly. We discuss the existing works introducing intelligence to the current 5G network architectures. Towards having an E2E embedded intelligence within the control, management and communication of the future 6G networks, we argue there is a need to establish synergy between the individual intelligent components. In essence, we discuss the ongoing issues and provide a strategy and framework to resolve those in this work. Driven by a vision of enabling E2E zero-touch network service automation at runtime, we propose a series of design objectives toward a framework for introducing ZSM natively into future 6G architectures. Specifically, this paper discusses the following:

- **Enabling native 6G intelligence:** The next generation of network architectures requires a model for native intelligence, which includes an orchestration framework and support for continuous training and faster deployment of the trained ML models via Transfer Learning (TL) [6] between real (testbed-based) 6G deployments and simulation environments.
- **Distributing 6G functionality up to the extreme edge:**The SDN/NFV paradigm allows the distribution of certain localised control, monitoring, and decision-making capabilities from centralised RAN (radio access networks) and MANO functions to the extreme edge, such as smartphones or IoT devices.
- **Exploiting technology leaps:**The adoption of multiple access technologies and peer-to-peer (P2P) communication between devices magnifies the benefits of a distributed 6G operation by avoiding round trips and optimising tasks offloading. It promotes better network availability and performance by increasing fault tolerance

and reducing bandwidth utilisation.

The present paper focuses our efforts on enabling native 6G intelligence while briefly discussing the other two pillars regarding multi-network integration and extreme-edge distributed control, as detailed above.

II. Background

The ZSM vision for automation requires end-to-end architecture with tailored ML-based Closed-Control-Loop (CCL) automation. This covers a major gap in the industry as well as in relevant academic research by converging the fragmented pieces into a single end-to-end service management design. CCL is an important aspect of achieving the ZSM goals, and some recent works have been proposed to enable CCL beyond 5G network architectures [7], [8]. As discussed in [7], ML is a key enabler of CCL. However, the following challenges still need to be addressed:

1) ML models generally require a large amount of data and a long time to train. The roll-out of new/updated ML models introduce some trade-offs to tackle in a CCL environment. Specially, high-quality datasets are limited to 5G scenarios [9]. Moreover, some existing ones are restricted due to privacy concerns [10].
2) The constraints found due to limited computational resources at the edge and extreme edge nodes make it difficult to train and update the models online [3], [9].
3) Existing network architectures were not designed to inherently support the ML components. It can result in overloading of the infrastructure when deploying resource-consuming ML solutions [3], [9].

There have been multiple efforts made to introduce intelligent and optimised placement of Network Functions (NFs) [3], [7], [10]. Some of the previous works have focused on introducing intelligence to the edge of the network to facilitate intelligent migration and scaling. However, intelligence is not well integrated into architectures and usually corresponds to ad-hoc efforts. In other words, in current architectures, the ML models are generally trained and hosted separately to facilitate network operations. The interoperability and deployment of VNFs across cloud and edge compute nodes is another aspect which needs intelligence to optimise the placement of NFs. Authors in [11] have presented a modular solution to achieve this. In 6G NFV architectures, we believe that such intelligent solutions can be well integrated within the CCL. This paper discusses the initial ideas towards addressing these challenges for native ML-driven networks, which are likewise presented in the following sections.

III. Architecture Aspects

A. Framework for continuous ML deployments

In order to address the challenges listed in Section II, we propose a close integration of the simulation environment with the CCL enabled production environment for ZSM. As shown in Figure 1 , the production environment consists of CCL in each domain (namely access, transport, cloud and edge/extreme edge as described in [7]).

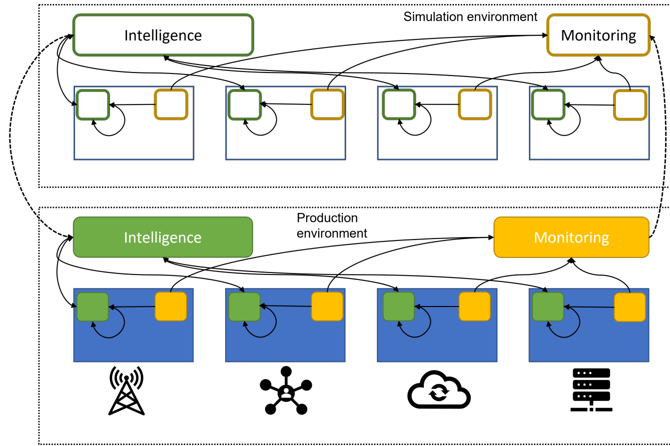

Fig. 1. Envisioned ZSM CCL with an integrated simulation environment.

With this framework, we propose replicating the production environment in the integrated simulator with configurations similar to the production environment. This would tackle the challenges from Section II by:

1) Large data generation (analogous to the production environment) using simulation and parallel training and evaluation to reduce the rollout time.
2) Continuous synchronisation of monitoring data from the production environment to enable efficient online training and update to the future advanced ML models.
3) Providing an experimental platform to create and evaluate new ML models utilising the high compute capacity.

Nevertheless, defining a proper stack for robust development, testing, deployment, and operation of ML models for next generation networks is not a trivial task. Different processes must be considered, such as data pre-processing and sanitation, model training, integration, and refinement.

We devise a **Unified Environment Interface (UEI)** to achieve these complex communication patterns between ML models and MANO services and processes for both simulation and the production environment.

The UEI adopts existing toolkits and methodologies, e.g., OpenAI-Gym [12], as the foundation of a standard API to leverage ML model integration, training, and refinement. OpenAI-Gym offers a common interface between *learning agents* (ML models) and managed tasks called *environments*. It is discussed that it is easier to use and extend existing frameworks like OpenAI-Gym as the ML research community widely adopts it to benchmark and compare ML algorithms rather than implementing a new standard. For instance, with OpenAI-Gym, it is possible to interact with environments exposing their observations, possible actions to be performed, states, and rewards used in the context of Reinforcement Learning (RL). The existing OpenAI-Gym interfaces are extended to train and deploy not only RL, but also other ML models for next-generation networks as a first step towards achieving the UEI. The previously mentioned claim will be demonstrated in the following section (Section IV).

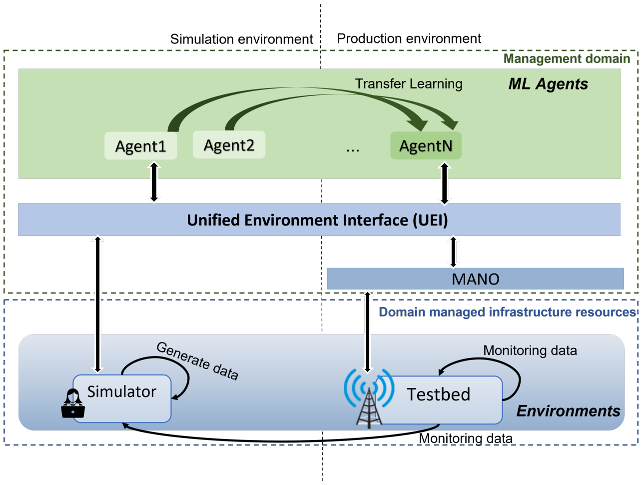

Fig. 2. Proposed framework for continuous ML deployment for ZSM using the Unified Environment Interface

The ZSM reference architecture [5] describes two interconnected domains: the managed infrastructure resources domain and the management domain. The former refers to physical resources (e.g., compute and network) and virtual resources (e.g., VNFs, Network Service) deployed on the infrastructure. Whereas the latter refers to management concerns such as intelligent automation orchestration, control, and assurance of resources. Figure 2 depicts the proposed framework. In this proposed approach, the managed infrastructure resources conform to the environments where actions and observations occur. The environments can include simulations, emulations, or real scenarios (e.g., testbeds). On the other hand, the management domain, which is part of the ZSM scope, corresponds to the administration of the resources to provide domain-level and cross-domain AI-inspired closed-loop automation.

The UEI is the bridge between the environments (i.e., managed resources) and the ML agents. In the case of simulations and emulations, observations, states, and actions are exposed in the standardised format directly to the simulator via UEI. Whereas, for the case of real-world scenarios (i.e., testbeds), this information can be exposed to the MANO via UEI. The MANO has access to the possible actions that can be performed in the managed resources and monitors their states and observations. Lastly, the ML algorithms are fed in a standard manner for their training and deployment. Standardising these interactions makes it possible to generalise and reuse ML approaches, monitor interactions for further processing, and enable smooth interaction between physical and virtual components.

One of the major challenges discussed in Section II is the lack of data for training ML models. This makes it difficult to speed up the rollout of updated ML models. With the proposed framework, if the integrated simulator is designed and configured as per the real environment, it could assist in decreasing the rollout time for the updated/advanced ML models. Such a framework would allow experimenters to create a real-world scenario and test multiple situations to generate data that could be used to train the ML models. Furthermore, by providing predictions, the framework can assist a MANO system in the placement of NFs along with scaling and migration. Likewise, by leveraging the integrated monitoring framework and having a holistic up-to-date view of the environment, the framework could also optimise the decision-making capability of the orchestrator.

B. Multi-access and Peer-to-Peer (P2P) communication

Along with the intelligent framework, the 6G architectures could leverage the existing TCP/IP technologies like Muti-Path TCP (MPTCP) to increase the overall bandwidth or robustness of the network by utilising all the available network interfaces in a User Equipment (UE). The extensions to MPTCP even allow to optimise and select low latency paths among multiple available options [13]. Edge deployments could benefit from this integration by reducing overall latency by prioritising the applications per the Service Level Agreement (SLA). Additionally, in 6G, we envisage the higher acceptance and integration of non-IP design concepts for protocols and NF technologies, such as those consistent with the Information-Centric Networks (ICN) architecture paradigm. ICN core principles such as the E2E and across all layers adaptation of publish-subscribe can enable the use of multi-access technologies to increase bandwidth and reduce latency [14] and other advantages mentioned above. ICN also introduces the in-network security aspects and seamless mobility based on the request-response methodology providing more options for the MANO and controller to achieve the desired performance. The closed integration of intelligent ML systems would enable an enhanced decision-making capability to select an optimum network technology to enhance the user's experience.

1) Using P2P communication between extreme edge devices as ad-hoc networks to minimise latency: In P2P networks, the nodes share their computation capacity along with the data among themselves in a symmetric and bidirectional manner. Similarly, mobile ad-hoc networks are generally self-managing and self-configuring networks [15]. Mobile ad-hoc networks are commonly short-lived and are created to serve a specific purpose. We expect that for certain 6G use-cases, the control shall be transferred to the network edge, including the extreme edge such as smartphones or other mobile smart devices. The underlying 6G network substrate enables nodes to build P2P networking relations across all layers (from application/service to physical layer connectivity). The applications like multi-player interactive gaming, which require extremely low latency and high bandwidth, could benefit from such a setup in a highly mobile environment. Enabling such self-organising pop-up networks would require the nodes to be P2P protocol aware. The integrated intelligent ML component could support MANO to delegate the localised network control to the edge/extreme edge nodes, which could set up the network and take decisions on the migration of containers/applications within the localised pop-up networks.

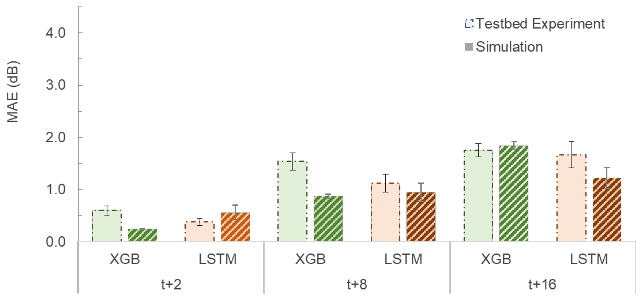

Fig. 3. MAE comparison using a custom simulation environment.

IV. Implementation and proof of concept experimentation

As discussed in Section II, one of the significant challenges for achieving integration of ML in ZSM is the lack of high-quality datasets for the training. Additionally, the deployment process can be disruptive. To address these challenges, we proposed in our framework a seamless integration of simulation environments and a next-generation testbed located at the University of Bristol, using a well-defined AI framework as UEI (i.e., OpenAI gym). The models trained in a simulator can easily be deployed in the real testbed using the concept of TL. TL could serve as an experimental playground for testing advanced ML models considering various network scenarios mimicking the real testbed. In this work, we have explored two ways to achieve this: Firstly, by creating a custom simulator with exact configurations as per the testbed, and secondly, by using a more generic simulator with some configurations as per the real testbed.

A. Custom simulator to support transfer learning

In our previous work [16], we developed a custom simulator to mimic the 5G radio network based on the ETSI standards. In addition, the simulator was configured according to the real outdoor testbed (using location parameters and radio configurations). Therefore, the simulator can generate random paths based on the conditions (walking, driving, cycling, etc.). In our experiment, we considered a user walking around the testbed while playing an interactive game. The UE is handed over from one radio access point to the other during this process. The ML model aims to predict the handover, in other words, to predict the likelihood of the mobile user being served from a particular radio access point in the near future. For this purpose, we trained the ML models to predict the Reference Signal Received Power (RSRP) of the radio access points.

Additionally, the Physical Cell ID (PCI) of the radio access point is decided using the predicted RSRP that would most likely be the next serving cell for the user. As shown in Figure 3, the predictions were made for 2, 8, and 16 seconds in the future. The radio monitoring data is continuously provided to the trained ML model to make predictions.

Using TL, we trained the two ML models in our experiment: eXtreme Gradient Boost (XGBoost) and Long Short-Term Memory (LSTM) neural networks, using a custom simulator and then deployed the trained ML models to predict the RSRP and Cell PCI in the real testbed. We used three 5G radio cells in the simulator, configured as per the real testbed, and generated random trajectories in the defined space. Results, updated from [16] in Figure 3 show that the difference between the Mean Absolute Error (MAE) observed in simulation and testbed experiments is relatively small ($\sim$0.5dB), hence supporting our arguments for using a proper (in this case, a custom) simulator that can serve as an ideal platform to speed up the painful and time-consuming ML life-cycle processes from model training to model deployment. Although the custom simulator works well during TL, it is still not in a closed loop with the production environment. Using the framework proposed from Section III, we aim to fulfil the gap by closely integrating the simulation and production environments in a closed loop with the ML components using the unified environment interfaces.

B. Community-standard simulation environment

To integrate the ML simulation environment with the real testbed, a set of well-defined APIs is required. Towards this regard, we tested the generalizability of our UEI approach, using the well-known NS3 discrete-event network simulator for Internet systems. NS3 is targeted primarily for research and educational use. NS3-gym [17] is an open-source project which interconnects OpenAI-Gym, with the NS3 network simulator using ZeroMQ (ZMQ). The framework allows seamless integration of Python scripts with simulation and offers functionality for synchronous and asynchronous communication, as well as direct benchmarking of RL solutions. Other than the feasibility of the seamless integration between ML system and a network simulator, we want to show the potential of the OpenAI-Gym interface beyond just the RL domain [17].

Figure 4 describes the proposed implementation. The environment encompasses the NS3 simulation ambient. Using the NS3-gym API and ZMQ, the communication between the Environment Gateway and the Environment proxy is established. This allows the simulation script, written in C++, to communicate during the simulation with the Python script where the ML agents are implemented. The previous mentioned allows the agent to interact with the environment through exposing observations of the states and actions to be performed in the simulation environment.

To test the feasibility of the approach, a similar experiment to the one from Section IV-A was performed using NS3. In this experiment, 2 supervised learning ML models were trained and tested with a simulation in NS3 (i.e., the environment) using the UEI. In contrast to the former experiment, we trained the recurrent neural network LSTM to forecast RSRP and Reference Signal Received Quality (RSRQ) of network cells based on observations of the environment exposed by the OpenAI-Gym API in the UEI. Then, the gradient boosting model XGBoost was trained to predict the serving PCI of the

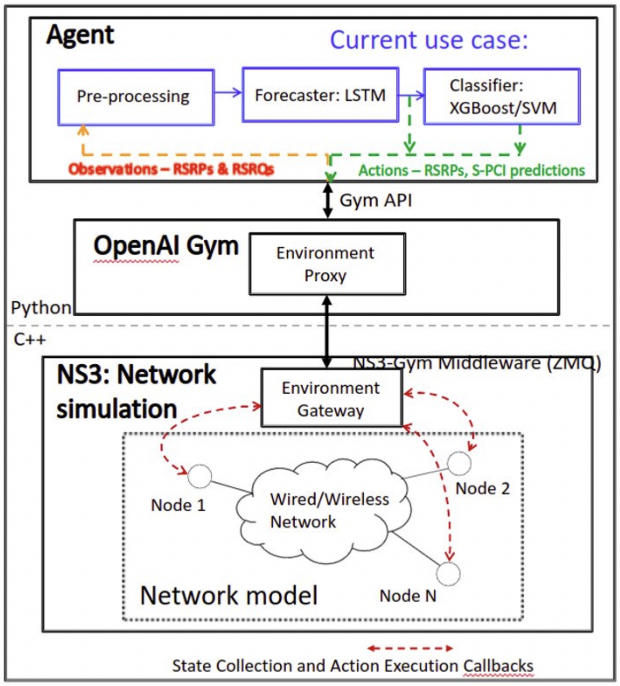

Fig. 4. NS3-OpenAI Gym interface

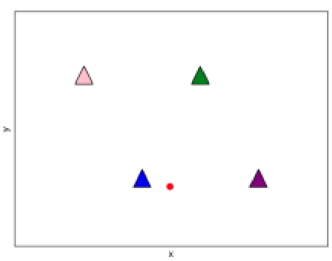

Fig. 5. NS-3 simulation: Cells and user distribution

user equipment at a certain point in the future, based on the outcomes of the LSTM network.

The experiment consisted of 4 base stations scattered on a plane representing a 5G microcell deployment. Figure 4 describes the scenario. Triangles represent base stations (cells), and the red circle represents a user equipment (UE) that changes its position dynamically to simulate user movements. The NS3 environment was initialized, and observations were collected from the simulation at each time step (0.5s) using a synchronous protocol. The observations consisted of the RSRP and RSRQ values of each cell, as a result of the implemented OpenAI-Gym specific callback functions. The performance of the LSTM model was evaluated by calculating the MAE of the model's predictions on the test set. The LSTM models were trained for different forecast lengths 4-cell 5G network scenarios.

Figure 6 (top) shows that small MAE values were achieved, ranging from 1.23 to 1.89db, which shows high predictive

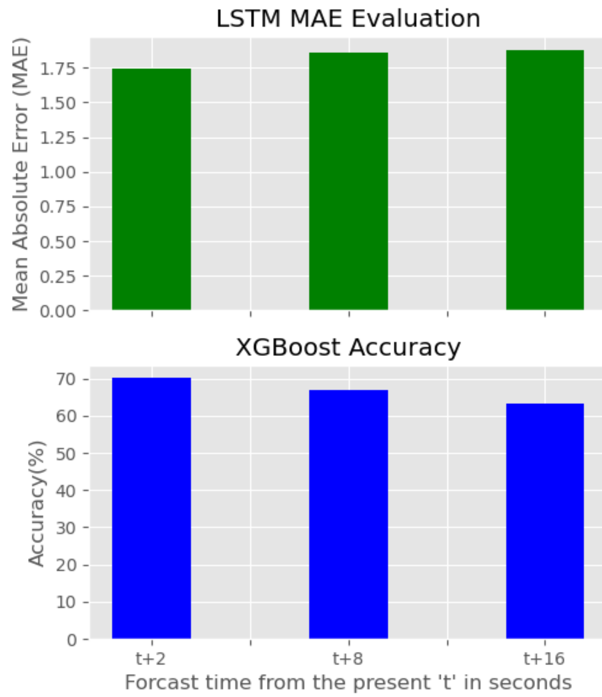

Fig. 6. MAE of the LSTM RSRP predictions (top) and XGBoost PCI prediction accuracy (bottom) for various forecast times.

performance. Regarding the XGBoost model, Figure 6 (bottom) shows that the model presented high accuracy scores for predicting the future serving cell or serving cell physical ID (S-PCI). The accuracy decreases as the forecast length increases, which is due to the uncertainty introduced when trying to predict points in the far future.

V. Conclusion and Future Work

In this article, we have described our vision toward a native Zero-touch 6G architecture design. Specifically, we have discussed three cornerstones for achieving this: i) enabling native 6G intelligence, ii) distributing 6G functionality up to the extreme edge, iii) exploiting technology leaps. We have focused our work on the first pillar towards introducing ZSM natively into future 6G architectures. In that regard, we have proposed a framework for continuous ML deployments based on a closed control loop between the simulation and production environment. The framework extends the ETSI ZSM reference architecture by defining a Unified Environment Interface (UEI) that acts as a bridge linking the managed resources, called environments, and the ML models, called agents, in the management domain. The proposed framework would not only allow a seamless and native integration of intelligence to the 6G networks, but also would expedite the rollout of new and updated ML models.

We adopted a two-fold testing approach, according to which, in the first experiment, we validated the TL using a custom simulator to address challenges 1 and 2 listed in Section II. Secondly, we used the proposed UEI framework through OpenAI-Gym to address challenge 3 by tightly integrating the ML and the simulation environments.

Future work will include research, development, and experimentation on the integration of UEI with the production environment. The close loop integration between the ML framework, simulation, and the production environments will be developed and tested. As discussed in this paper, we envisage the framework as an enabler for further research on designing novel AI-optimised6G multi-network technologies and extreme edge distributed control.

VI. Acknowledgements

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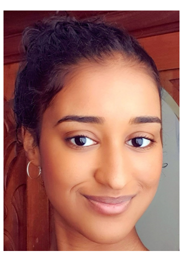

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