Proactive Anomaly Detection in Network Slicing in the realm of Intelligent Transport Systems through leveraging EdgeApps

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***Abstract*—This paper outlines important limitations of current Edge Network Applications (EdgeApps) in effectively monitoring and adapting to the fluctuating conditions of 5G and beyond networks, emphasizing the imperative for EdgeApps to evolve into entities with full network awareness to bolster vehicular teleoperation's safety and efficiency. The ultimate goal of the research aims to advance current knowledge on Machine Learning (ML) algorithms for monitoring network slice behaviour and develop a proof-of-concept EdgeApp capable of proactively detecting anomalies and initiating network changes, ensuring an optimal quality of experience for vertical services in the advent of next-generation networks. Through this ongoing research, we aim to propel the development of fully network-aware EdgeApps by demonstrating a unique application scenario and examining diverse AI/ML algorithms to foster proactive network management strategies.**

***Index Terms*—5G and beyond, AI/ML, EdgeApp, Teleoperation, Edge computing, Slicing**

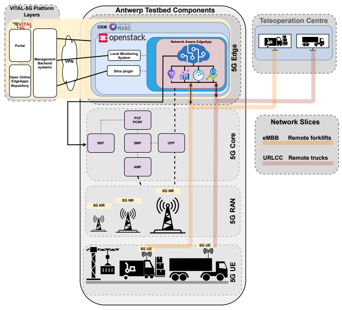

Fig. 1. Network Slice Monitoring with Intelligent intend based Network Aware EdgeApp.

I. Introduction and Motivation

The Edge Network Application (EdgeApp) framework, developed under the VITAL-5G project[1] (ICT-41 EU project) [1], has the potential to accelerate the adoption of complex 5G and beyond vertical services across various industries such as Transport & Logistics (T&L), automotive, among others. This is crucial as these industries currently lag behind in adopting 5G technologies and understanding their potential to enhance day-to-day operations. The European Commission has financed the VITAL-5G project to expedite the growth, adoption, and economic benefits of EdgeApps in the T&L vertical. EdgeApps serve as important building blocks for creating network services for vertical industries [1].

The EdgeApp framework enables vertical industries to define their network, service, and hardware requirements through the EdgeApp blueprint [1]. These specifications are then interpreted by network controllers and orchestrators, facilitating changes and service deployments according to the outlined blueprints. Our ongoing research on EdgeApps has demonstrated their ability to dynamically create events triggering changes in Quality of Service (QoS) in real-time, leveraging Nokia's Network as Code (NaC) solution. Nokia NaC solution enhances and exposes open-source CAMARA[2] Application Programming Interfaces (APIs), defined by the GSMA-initiated[3] Open Gateway Initiative (OGI), to deliver the necessary QoS levels for vertical services. In this way [4], EdgeApps can dynamically reprogram the underlying 5G network during specific events via standardized APIs, potentially making them deployable on any network worldwide. Thus, the EdgeApp framework is placed to become the cornerstone of a comprehensive middleware platform, facilitating seamless communication between vertical applications and 5G/6G Core networks while shielding users from underlying network complexities.

[1] VITAL-5G: https://www.vital5g.eu/
[2] CAMARA: https://camaraproject.org/
[3] GSMA: https://www.gsma.com/
[4] QoS EdgeApp: https://www.imec-int.com/en/articles/beyond-speed-real-promise-5g-lies-demand-qos

However, a significant limitation of existing EdgeApps is their inability to intelligently monitor the underlying 5G and beyond network (Fig. 1). While they can communicate their network requirements, through their EdgeApp blueprint, and dynamically reprogram the network through CAMARA APIs in certain events, they lack the capability to monitor network behaviour in real-time and thus be able to proactively detect future events (Fig. 1). This gap is particularly noteworthy as there exists a discrepancy between the network performance perceived by network controllers in the 5G networks and the actual user experience of connected User Equipments (UEs) (e.g., vessels, vehicles, etc.). Positioned at the Edge of the 5G and beyond network, EdgeApps have the potential to bridge this gap by accessing the same network information as connected UEs. By leveraging intelligent Artificial Intelligence (AI)/Machine Learning (ML) algorithms, EdgeApps can monitor specific network slices hosting vertical services. Subsequently, they can dynamically issue intend-based commands to the underlying 5G and beyond network, either through Nokia's NaC or CAMARA APIs directly, to initiate reprogramming. This capability enables EdgeApps to effectively manage and orchestrate slice performance tailored to the requirements of vertical services. EdgeApps that are fully network aware in an intelligent manner could unlock a multitude of new possibilities, to name a few:

- **Enhancing existing 5G Core network monitors**: Allowing EdgeApps to monitor the actual performance of the slices consumed by vertical services can enhance existing network monitors. Currently, existing network monitors lack direct awareness of the slice performance experienced by the vertical services. By bridging this gap, EdgeApps can augment existing network monitors with insights into the actual network performance perceived by the vertical services.
- **Quality of Experience (QoE) Optimization**: Fully network-aware EdgeApps have the potential to tailor their behaviour based on the perceived Quality of Experiences (QoEs) of vertical services. By continuously monitoring network performance metrics, EdgeApps can dynamically adjust the required performance of slices to ensure consistently high QoE for vertical services.

- **Real-time Network Optimization**: With network awareness, EdgeApps could continuously monitor the slice performance metrics such as latency, throughput, and packet loss. They could then dynamically adjust their behaviour and resource allocation to optimize application performance in real time. For example, if congestion is detected in a specific network slice, EdgeApps could ask the underlying network to change the QoS parameters of the slice accordingly or to proactively create a new slice.
- **Predictive Maintenance**: By analyzing historical network data of a slice and leveraging ML algorithms, network-aware EdgeApps could predict potential network slice failures or performance degradation before they occur. This could enable proactive maintenance actions to be taken, reducing downtime and improving overall reliability.
- **Enhanced Security and Privacy**: By monitoring network behavior in real-time, EdgeApps could detect and mitigate security threats more effectively. For example, they could identify abnormal patterns of traffic indicative of a potential cyberattack and take proactive measures to block or mitigate the threat. Additionally, network-aware EdgeApps could ensure data privacy by dynamically encrypting sensitive traffic based on network conditions and security policies.

For the reasons mentioned above, and to enable EdgeApps to become fully network aware, the first research step is to explore various AI/ML algorithms. We have provided an overview of these algorithms in this paper.

II. Setup and Use Case

The ultimate goal of the research aims to advance current knowledge on AI/ML algorithms for monitoring network slice behaviour and develop a proof-of-concept EdgeApp capable of proactively detecting anomalies and initiating network changes. To validate these findings in a real-world 5G Standalone (SA) network, the Antwerp VITAL-5G testbed is utilized (Fig. 1). This testbed features a live 5G SA network with Ultra-Reliable Low-Latency Communication (URLLC) and enhanced Mobile Broadband (eMBB) slices, along with an Edge platform connected to the 5G Core via a 7.2 km optical fibre (Fig. 1). Leveraging this infrastructure enables the validation of both simulated and real-life results, providing a comprehensive assessment of the proposed AI/ML algorithms

In the automotive sector, the future of mobility will involve a mix of autonomous, teleoperated, and conventional vehicles. Situational awareness among all traffic participants will be crucial for ensuring safety. For autonomous vehicles, ensuring sufficient bandwidth dynamically becomes essential, especially in situations where remote control is necessary to handle edge cases beyond the vehicle's capabilities (Fig. 1). Our proof-of-concept (PoC) will focus on this specific use case, where a fully network-aware EdgeApp can proactively monitor the network slice carrying the remote camera feed of a teleoperated vehicle (Fig. 1). It will ensure that the slice consistently meets the requirements specified in the application blueprint, guaranteeing safety at all times. In the case these requirements are not met, the network-aware EdgeApp will generate intents to be communicated to the 5G and beyond network.

III. AI/ML algorithms

In the context of designing the EdgeApp tasked with monitoring the compliance of 5G and beyond network requirements and performances, the selection of the most appropriate AI/ML algorithm holds paramount importance. AI encompasses various paradigms, each tailored to address distinct learning scenarios and objectives. The subsequent AI learning types are deemed suitable for EdgeApps within our use case [2] [3]. These types are suitable for our EdgeApps because they can predict a scenario based on previous data and measured network performances.

- **Supervised Learning (SL)**: Operating on labeled data, this learning paradigm enables algorithms to predict outcomes based on input-output pairs. Through training on a dataset with known outcomes, models gain the capacity to generalize and make predictions on new, unseen data. Supervised Learning (SL) refers to ML algorithms.
- **Reinforcement Learning (RL)**: Involving an agent's learning process through trial and error within an environment, Reinforcement Learning (RL) aims to maximize cumulative rewards. By interacting with the environment, the agent receives feedback in the form of rewards or penalties for its actions.
- **Transfer Learning (TL)**: This approach seeks to transfer knowledge from a source domain to a target domain, even when data may be scarce. Rather than initiating training from scratch, pre-trained models are fine-tuned or adapted to the target task, thus conserving time and computational resources.
- **Ensemble Learning (EL)**: This type encompasses the amalgamation of multiple base learners to construct a more robust model. By capitalizing on diverse perspectives from individual models, ensemble methods frequently outperform single models. Techniques such as bagging, boosting, and stacking are commonly employed within Ensemble Learning (EL).

In addition to these learning paradigms, there exist various ML algorithms that can be employed within these AI learning types. AdaBoost, Random Forest (RF), and Recurrent Neural Networks (RNNs) are prominent ML algorithms used in various applications.

- **AdaBoost**: This boosting algorithm sequentially trains a series of weak learners, with each subsequent learner focusing on the mistakes made by its predecessors.
- **Random Forest (RF)**: Employing an ensemble learning method, RF leverages the power of decision trees to improve predictive performance and robustness. RFs train multiple decision trees independently on bootstrapped samples of the training data and aggregate their predictions through averaging or voting.
- **RNN**: Belonging to a class of artificial neural networks, RNNs are designed to process sequential data by maintaining internal state or memory. Distinguished from feed-forward neural networks, RNNs feature connections that form directed cycles, enabling them to capture temporal dependencies in sequential data.

In our current phase of research, Ensemble Learning emerges as the most viable candidate for integration within our EdgeApp framework. This classification method within AI leverages techniques such as AdaBoost and RF.

IV. Conclusion and Future Work

In this paper, we motivated why EdgeApps need to become fully network-aware in the near future. We presented a novel use case where fully network-aware EdgeApps will be a necessity in order to guarantee the safe teleoperation of vehicles (Fig. 1). To then present an overview of the first steps we are making towards making this vision a reality with the possible AI/ML algorithms that potentially could be incorporated into our proposed EdgeApp.

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