Enhancing Radio Access Network Slicing via Machine Learning Predictions

(PhD Studentship Proposal)

Background

Networks are currently required to dynamically adapt to meet the distinct requirements of diverse traffic classes. Emerging classes of traffic such as those generated by autonomous vehicles and various machine-to-machine communications are adding another dimension to the already congested wireless channels [1]. To meet the requirement of this class diversity and high demand, slicing the radio access network (RAN), which complements core and transport slicing, has gained significant popularity, both from academia and industry [2]. In fact, there are now a number of network equipment manufacturers offering different forms of slicing capabilities, but we are yet to see the full potential of this exciting concept. And despite these available options in the market, end-to-end network slicing remain in the development phase and largely still under investigation. However, it is expected to dominate future network access mechanisms, both in the core and the edge of the network.

Motivation

Network slicing is an approach to provide separate independent end-to-end logical network from user equipment (UE) to applications where each network slice has different Service Level Agreement (SLA) requirements. Although slicing has many advantages in terms of end-to-end network resource management, giving the dynamic nature of cellular networks, it is a challenging problem to provide an optimum allocation for the various classes of traffic at the edge of networks [3]. At present, most RAN slicing approaches are based on static splitting of the spectrum bands, which is an inefficient method [4]. This can leave many users experiencing durations of outages in the case of imbalanced slice allocations. For applications such autonomous vehicles, which have strict delay bounds, any number of outages of any duration can have catastrophic consequences. On the other hand, over allocation of spectrum, could generate high bills for virtual network providers.

In addition to the above, cellular networking technologies are becoming increasingly smaller, due to the inclusion of new mmWave spectrum bands and to maximise spacial reuse. As a result, more cells are required to be deployed to provide adequate coverage. This in turn, complicates network management and make static slicing techniques less useful. To make matters worse, to utilise static RAN slicing, service providers must determine in advance their network resource requirements to cope with their diverse future demands.

Proposed research

The unpredictable and dynamic volume and nature of traffic demand is one of the most challenging issues that real-world implementation of RAN slice (aka RAN sub-slice) will likely to face. Making a reliable and robust prediction is hard without some knowledge of the future. It is hard for an operator to predict, with low error probability, how long they will require a particular slice to support the demand that might arrive in the future. In this context, there are many machine learning (ML) solutions which are aimed at managing uncertainty. Such solutions are typically achieved through examining past data and building robust models. These models are then utilised to predict future demands. This technique have been successfully employed to model problems such as caching and job scheduling [5]. However, to the best of our knowledge, there are no known studies that have examined the potential of ML techniques in predicting RAN slicing demand at the edge of networks. In this context the project will first, aim at identifying possible ML systems that could be deployed close to antenna to manages the real-time air interface resources and to predict diverse slicing demands of e.g., virtual network and over-the-top (OTT) service providers, enabling what is called slice awareness [6]. Second, provide comparative analysis to determine efficiency and time complexity of identified ML systems. The research will first be carried out using simulation platforms such as MATLAB, which are optimised for ML tasks, to prove the concept. Followed by real-world implementations across various virtual systems.

Potential impact

The analysis will determine which ML algorithms are most suitable to provide fast and easy real-world implementation in the edge of the network. This could make a valuable contribution towards minimising the operation expenditure of virtual operators. Another critical impact will be optimising spectrum allocation, alleviating radio resource shortages. Since this approach can be built using software alone in form of virtual controllers, testing and implementation in real-world networks will be less complex and will not rely on development of other hardware technologies such as antenna and other front end components. The research can be further extended to enhance slice orchestrators which interact with controller of RAN, Core and Transport slices, for mapping purposes.

References

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