A Softwarized Service Infrastructure for the Dynamic Orchestration of IT Resources in 5G Deployments

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ABSTRACT

Thanks to the 5G, telco operators can offer a new set of advanced services to mobile users which makes use of heterogeneous IT resources deployed at the edge of the network. However, their optimal management is not a simple task to accomplish because of the extreme variability characterizing offered services, traffic profile, user distributions, bandwidth, computing, and memory capabilities available for nodes hosting IT resources. To provide preliminary answers in this direction, this paper presents a high-level description of a softwarized service infrastructure, based on the ETSI-NFV specifications, able to dynamically orchestrate IT resources. Specifically, the number of users attached to the base stations and the capabilities of nodes hosting IT resources are continuously monitored through Software-Defined Networking facilities and reported to a high-level orchestrator. Here, a Convolutional Long Short-Term Memory scheme is firstly adopted to provide a spatio-temporal prediction of user distributions and related traffic demands. Then, an optimization problem is executed for configuring location, settings, amount, and usage of IT resources, based on the prediction outcomes. The behavior of the prediction process is deeply investigated. The optimization problem, instead, is described in its preliminary formulation, which gives a clear idea of future research activities in this direction.

Keywords: Software-Defined Networking, ETSI-NFV, Network Optimization, Deep Learning.

1. INTRODUCTION

The integration of Software-Defined Networking (SDN) and Network Function Virtualization (NFV) technologies offers concrete opportunities to develop the fifth generation (5G) of mobile networks, ensuring high performance in terms of scalability and rapid time to market. In this context, telco operators can offer a new set of advanced services to mobile users, which makes use of heterogeneous IT resources deployed at the edge of the network, while increasing the network programmability and reducing CAPEX and OPEX. In this context, however, the optimal management of IT resources represents a very challenging task to accomplish because of the extreme variability characterizing offered services, traffic profile, user distributions, and the availability of bandwidth, computing, and memory capabilities for nodes hosting IT resources [1], [2].

In the scientific literature, resource management and allocation tasks (i.e., computation offloading, joint communication and computing resource allocation problem) have been addressed through various optimization algorithms focusing on different objectives, ranging from the minimization of the energy consumption or the delay to the maximization of the quality of service [3]. Most of these contributions take decisions by only considering the current knowledge of the network configuration and conditions. Nevertheless, network optimization can be improved by introducing deep learning techniques, properly tailored to anticipate traffic and mobility patterns [4], [5]. Prediction tasks are generally investigated separately in the current state of the art. Traffic forecasting has been achieved through Convolutional Neural Networks (CNNs), Long Short-Term Memories (LSTMs), or a combination of them [6]. Mobility has been predicted through Markov Chains, Markov Decision Processes, Hidden Markov Models, Bayesian Networks, or Neural Networks for trajectory and location prediction, or a combination of Neural Networks and Bayesian Networks for the prediction of user distributions [7]. A first attempt that jointly performs traffic and mobility prediction by means of a multivariate LSTM architecture is presented in [8]. Nevertheless, at the time of this writing, no contributions consider the usage of this promising instruments for the optimal management and allocation of IT resources in 5G deployments.

Starting from a preliminary contribution presented in [9] by the same authors of this work, this paper extends the current state of the art by proposing a softwarized service infrastructure, based on the ETSI-NFV specifications, which dynamically configures and orchestrates IT resources available in 5G deployments. Specifically, the number of users attached to base stations and the capabilities of nodes hosting IT resources are continuously monitored through SDN facilities and reported to a high-level orchestrator. The Convolutional Long Short-Term Memory (ConvLSTM) scheme is firstly adopted to provide a spatio-temporal prediction of user distributions and related traffic demands. Then, an optimization problem is executed for configuring location, settings, amount, and usage...
of IT resources, based on the prediction outcomes. This proposal can be safely implemented also in a large-scale scenario where base stations and network routers are managed by a multi-layer controller structure. In this case, SDN controllers can communicate with a parent controller, before reporting the number of users attached to base stations and the capabilities of nodes hosting IT resources to the orchestrator.

The remainder of the paper is as follows. Section 2 illustrates the proposed service infrastructure. Section 3 presents the behavior of the prediction process by considering three possible use cases. Section 4 provides some guidelines for the design of a network optimization algorithm implemented by the orchestrator. Finally, Section 5 concludes the paper and draws future research activities.

2. THE PROPOSED SERVICE INFRASTRUCTURE

The softwarized service infrastructure presented herein aims at dynamically orchestrating IT resources in 5G deployments, supporting a wide range of applications. E-Health, autonomous driving, and augmented/virtual reality are possible examples of applications with different communication and computing requirements (see Table 1). Note that the latency requirement, ranging from 1 ms to 100 ms [10], is a highly critical aspect to be taken into account for the design of the orchestration framework.

Table 1. Use case requirements.

| Use case               | Latency    | Bandwidth  | Memory  | Computation |
|------------------------|------------|------------|---------|-------------|
| e-Health               | 1-10 ms [10] | 100 Mbps [10] | 8 GB [11] | 1.2 GHz [11] |
| Autonomous Driving     | 10-100 ms [10] | 700 Mbps [10] | 16 GB [12] | 2.1 GHz [12] |
| Virtual Reality        | 1 ms [10] | 1 Gbps [10] | 32 GB [13] | 3.5 GHz [13] |

Fig. 1 shows the proposed service infrastructure. It embraces different domains, whose network equipments are managed by a single SDN controller, namely the domain controller. At the large-scale, the configuration of different domains can be managed through a hierarchical and highly scalable architecture of controllers [10]. Specifically, multiple domain controllers, that are connected to base stations, nodes hosting IT resources, and network routers, are specialized controllers in charge of intra-domain services. They are coordinated by a parent controller or directly orchestrated by the network orchestrator, which interoperates with domain controllers to provide end-to-end and inter-domain services. The system model described herein simply considers base stations and network nodes belonging to a single domain. However, it can be safely extended to describe the aforementioned hierarchical scenario.

Figure 1. The proposed service infrastructure.

The set of base stations available within the considered domain is denoted with \( J \). At the same time, the set of users attached to the \( j \)-th base station is denoted with \( I_j \) and the whole set of users \( I \) is given by their combination. Based on the targeted application, the \( i \)-th user requests a communication bandwidth of \( b_i \) and an upper bound of the communication latency equal to \( \tau_i \), as well as IT resources with memory and computing capabilities equal to \( m_i \) and \( c_i \), respectively. At the edge of the network there are \( N \) nodes hosting IT resources. Given the \( n \)-th node belonging to \( N \), its memory and computing capabilities are identified with \( M_n \) and \( C_n \).

The role of the SDN controller is to periodically monitor the number of users in \( I_j \), attached to each base station, the communication bandwidth available between the \( j \)-th base station and the \( n \)-th node hosting IT resources, and the computation and memory capabilities available for the \( n \)-th node hosting IT resources. This information is delivered to the high-level orchestrator for predicting the user distribution and related traffic demands in future time instants and performing the optimal allocation of IT resources among mobile users. The outcomes of the allocation problem are used to configure the whole softwarized service infrastructure through SDN facilities.
3. PREDICTION OF USER DISTRIBUTIONS AND RELATED TRAFFIC DEMANDS

Spatio-temporal distributions of users are captured by SDN controllers and collected by the orchestrator, which can consequently perform the prediction of user distributions and related traffic demands. Specifically, the prediction architecture adopted for this purpose is based on the ConvLSTM scheme, that exploits LSTM memory cells and the convolutional operation, through which it can extract temporal and spatial correlations of data, respectively [9]. The predicted number of users attached to different base stations is then used to quantify bandwidth, computing, and memory requirements to be taken into the account by the optimization algorithm.

The adopted dataset refers to a one-month distribution of taxi cabs in the center of Rome. The considered geographical area of around 110 km² has been divided using 11 × 10 square cells, so that the j-th grid cell, attached to the j-th base station, covers a square area of 1km × 1km. Fig. 2 shows the predicted number of users attached to two reference base stations (i.e., j = 45 and j = 55). Furthermore, by assuming that each user enjoys, at the same time, e-Health, autonomous driving, and virtual reality services, the aggregate requests of communication and computing resources coming from the two reference base stations are depicted as well.

![Figure 2. Predicted number of users and aggregated communication and computing resources estimated for e-Health, autonomous driving, and virtual reality use cases for (a) j = 45 and (b) j = 55.](image)

4. PRELIMINARY CONSIDERATIONS FOR THE NETWORK OPTIMIZATION

This Section provides a preliminary formulation of the optimization problem that considers the communication latency as the main objective for configuring location, settings, amount, and usage of IT resources. The overall latency \( l_{ijn} \) experienced by each user \( i \), connected to the j-th base station and served by the n-th node hosting IT resources, can be considered as the sum of three contributions [10]:

\[
l_{ijn} = l_{ij}^{\text{radio}} + l_{ijn}^{\text{backhaul}} + l_{in}^{\text{execution}},
\]

where \( l_{ij}^{\text{radio}} \) is the radio interface component, \( l_{ijn}^{\text{backhaul}} \) is the backhaul latency between the j-th base station and the n-th node hosting IT resources at the edge of the network, and \( l_{in}^{\text{execution}} \) is the execution latency required to the specific n-th node hosting IT resources for serving the user \( i \).

The preliminary formulation of the optimization problem executed by the orchestrator is provided in Table 2. The reported considerations will be deeply investigated in future research activities.

| Table 2. Considerations related to the optimization problem. |
|-----------------------------------------------|-----------------|-----------------|
| **Aspect** | **Analytical formulation** | **Description** |
| Possible optimization objective | \[
\min_{a_{in}} \left\{ \sum_{j \in J} \sum_{i \in I} \left[ l_{ij}^{\text{radio}} + \sum_{n \in N} a_{in} (l_{ijn}^{\text{backhaul}} + l_{in}^{\text{execution}}) \right] \right\}
\] | Given the predicted number of users attached to each base station \( I_t \), the optimization problem could minimize the latencies experienced by users. |
| Constraints on memory and computation capabilities | \[
\sum_{i \in I} a_{in} m_i \leq M_n, \forall n \in N
\]
\[
\sum_{i \in I} a_{in} c_i \leq C_n, \forall n \in N
\] | The number of users served by the n-th node cannot exceed its memory and computation capabilities. |
5. CONCLUSIONS

This work has presented a softwarized service infrastructure, based on the ETSI-NFV specifications, able to dynamically configure and orchestrate IT resources. We have performed the spatio-temporal prediction of user distributions and related traffic demands through a Convolutional Long Short-Term Memory scheme. Then, the outcomes of the prediction process have been thoroughly examined by considering e-Health, autonomous driving, and virtual reality use cases. Moreover, the prediction outcomes have been adopted to sketch an optimization problem to minimize the overall latency experienced by mobile users and consequently configure IT resources hosted in edge nodes. Further research activities will operatively implement optimization algorithms, exploiting the prediction process to anticipatory orchestrate the network infrastructure.

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