A Multi-Criteria Decision Making Method for Network Slice Edge Infrastructure Selection

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***Abstract*—In the era of 5G networks, the demand for high quality service provisioning is growing extremely fast. The enabling of Network Function Virtualization and Network Slicing in the scope of 5G network aims to meet the strict requirements of various business cases. Alongside, the complexity of deployment such services becomes also higher, regarding the differences between infrastructure capabilities and the plethora of various individual requirements. This fact makes the selection of the appropriate infrastructure for slice deployment a complex, but also, a major process, as the optimization of the selection leads to the satisfaction of the user and the better resource allocation from the provider's perspective. In this work, an Edge PoP Selection framework for network slice deployment is proposed. This framework takes into account the user's hard and soft requirements and performs a two-stage selection. The selection of the appropriate infrastructure is based on a multi-criteria decision making method. The proposed framework is evaluated and compared with simple filtering and single-objective selection approaches. The promising results show the importance of the two stage framework in order to simultaneously meet the user's requirements and the optimal utilization of the resources.**

***Index Terms*—Network Slicing, MCDM, Fuzzy AHP, Cross-Slice Communication, Edge Computing**

I. Introduction

The advent of 5G networks allows the deployment and orchestration of various vertical use cases. Network Function Virtualization (NFV) [1] and Software-Defined Networking (SDN) [2] paradigms enable the deployment of complex network services on generic hardware in the form of network slices. A network slice consists of interconnected Virtualized Network Functions (VNFs), which host one or more applications. The initial definition of NFV refers explicitly to network services such as firewall, routing and load balancing. Furthermore, the major advantages of network slices are the control of the allocated computing and network resources and the isolation of their components, which can guarantee the high performance of the network slice. The deployment, orchestration and management of the network slices in a cloud data center is a challenging and complex task and many software solutions, e.g. Open Source MANO [3] and OpenStack [4], aim to facilitate the automation of the whole process.

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Cloud computing is the dominant application delivery paradigm and is tightly connected with the deployment of the network slices. In the 5G era, the smart applications rely mainly on mobile end-devices that have limited computing capabilities to guarantee the strict application's performance requirements in terms of network latency. Thus, the cloud computing paradigm shifts to the new model of Edge Computing [5], which provides computing facilities at the edge of the network. Due to limited resources of the edge infrastructure, the network slice placement problem must consider the dynamic features of the network slices in terms of workload and scalable resources [20]. With this capacity, the network slice definition must extend and include any type of applications. Furthermore, the careful relaxation of the network slice isolation can facilitate the Cross-Slice Communication (CSC) inside an edge data center in order to guarantee low network latency and optimize the resource allocation policy [6].

In this modern cloud environment, a network slice can be deployed in one of many available edge Points of Presence (EPoPs). The selection of the appropriate EPoP is not a straightforward task and depends on many performance, cost and support requirements of the slice owner. Thus, a single-objective decision method would not select an optimal solution. On the other hand, many multi-criteria decision making (MCDM) approaches have been proposed for the cloud provider selection problem [9], [12] for the deployment of cloud services. These methodologies take into account various types of Key Performance Indicators (KPIs) and rank the candidate providers. Furthermore, they enable the service owners to adjust the individual weight of every criterion based on their hard and soft requirements.

In this study, we propose an Edge PoP Selection Framework (EPSF) that aims to facilitate the deployment of network slices. The EPSF focuses on the network slice deployment in EPoPs and the accommodation of the CSC. Toward this direction, the EPSF considers two stages of selection. Initially, based on hard requirements of the slice deployment (location and CSC ability), a group of candidate EPoPs is created. Then, a multi-criteria decision making method, namely Fuzzy Analytic Hierarchy Process (FAHP) [7], considers various performance, cost and support criteria to rank the candidate EPoPs and select the one that satisfies at most the soft constraints of the slice owner. The evaluation of the EPSF under a realistic scenario and its comparison with simple filtering and single-objective methods demonstrates that the proposed approach is scalable and generates optimal solutions.

The rest of the paper is organized as follows. In Section II, the current state of the art is presented. Section III demonstrates the architecture and component of the EPSF, while Section IV presents the evaluation of the proposed framework and a discussion of the results. Finally, Section V draws the conclusions and refers to future work.

II. Related Work

Regarding the dominant aspects of network slicing, the interested reader can refer to [8]. This section presents the most relative multi-criteria studies on cloud and network slice provider selection.

Garg et al. [9], [10] defined a quality model for assessing Infrastructure as a Service (IaaS) providers that includes various quantitative KPIs and attributes. The ranking system is based on AHP, which provides a weighted hierarchical structure of the attributes and KPIs and computes the relative ranking values of the candidate cloud providers. However, these approaches cannot process qualitative KPIs. Towards this direction, many fuzzy MCDM approaches have been used to solve various version of the cloud selection problem. Papadakis et al. [11] applied the FAHP approach to select the appropriate provider in a cloud federation. This approach provided a SLA framework and processed evaluations of previous users of a cloud infrastructure to produce a reputation score for each cloud provider. Based on SLA and monitoring data, a credibility mechanism was designed to alleviate the effect of malicious assessments. In [12], the authors proposed a modified fuzzy VIKOR approach for facilitating the resource selection in a federation of heterogeneous testbeds. Since Fuzzy VIKOR is based only in fuzzy KPIs, any numeric KPI is transformed to fuzzy one. Then, the evaluation of the users is compared with the assessment of a virtual user, which evaluates with the best score for each KPI, in order to update the reputation value of the testbed. In this work, the user of the infrastructure assign their individual weights to the KPIs depending on the requirements of their service to be developed. CLOUDQUAL model [13] defined six quality dimensions for cloud services and evaluated them on three commercial storage clouds. For validation purposes, three criteria were used, i.e., correlation, consistency and discriminative power, following IEEE standard for a software quality metrics methodology [14]. Li et al. [15] proposed a broker-based trust scheme for resource matchmaking across multiple clouds. This approach is based on various numeric service operators, such as security, availability and reliability over specific time windows. Contrary to other studies, the trust attributes are not assigned subjectively by the users but they are computed by an entropy-based methodology. Finally, the authors of [16] proposed a multi-criteria method for placing network slices. Each infrastructure provider built reference slice blueprints and mapped them into many slice instances. Then, a vector of criteria is constructed for each candidate slice and the TOPSIS algorithm is used for the ranking of all candidate instances.

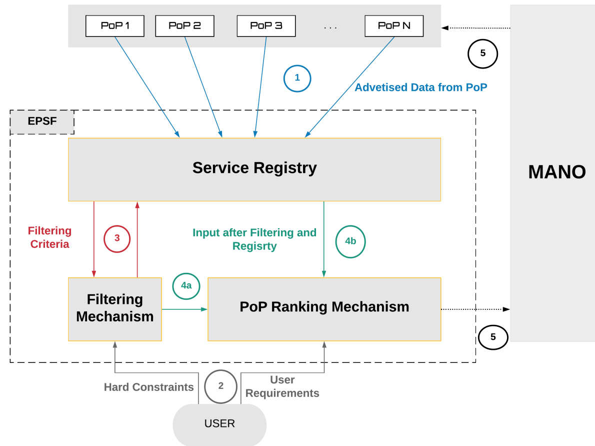

Fig. 1. Edge PoP Selection Framework

Beyond the above studies, the proposed EPSF is based on both qualitative and quantitative criteria and focuses on services deployed on edge clouds and cross slice communication. The two stages of EPSF aim to guarantee firstly any hard deployment constraint of the network slice and secondly select the most appropriate EPoP among the candidates based on various performance, cost and support criteria.

III. Edge PoP Selection Framework

This section presents the proposed Edge PoP Selection Framework, which is based on the multi-criteria decision making method of FAHP. EPSF is designed to meet a set of user's requirements on selecting the appropriate PoP at the edge of the network for deploying a network slice. Based on the user's inputs and the advertised data from EPoPs, the two-stage selection procedure filters and ranks the candidate EPoPs in order to meet the user's requirements and enable the optimal resource provisioning from the provider's perspective. Figure 1 shows the architecture of the framework and the appropriate tools to make it applicable on a large scale are presented below.

A. Proposed Architecture

Focusing on the automated deployment of network slices, we assume a cloud provider that controls several geographically distributed EPoPs. Under this setting, we propose an architecture which settles the following key functional requirements: (i) the needed data for the EPSF has to be advertised from each EPoP for the respective ranking criteria, (ii) the user has to express the requirements in the form of several KPIs and attributes. Towards this direction, the proposed architecture is based on the following components:

TABLE I
EPSF KPIS DEFINITION [9]

KPI name	Definition
Availability	The percentage of time a customer can access the service
Service Response	VM provisioning and booting time, assigning an IP address and starting application deployment
Elasticity	The maximum number of compute units that can be provided at peak times
Bandwidth	The minimum rate of data transfer, measured in Mbits per second
VM Cost	Virtual machine acquisition cost
Data Cost	Virtual machine on going cost for network resources
Document Readability	The provision of efficient documentation about the tools for slice deployment
Technical Support	The provision of 24/7 technical customer support about deployment and other services issues

- **Service Registry**: This component is responsible for collecting the necessary advertised data from each EPoP and details about the ranking criteria, which are used for the ranking process. As the Step 1 of Figure 1 shows, the EPoPs advertise their values on predefined KPIs by the cloud provider to the centralised Service Registry.
- **Filtering Mechanism**: The user's requirements are separated to hard and soft ones. The hard requirements must be definitely satisfied and refer to EPoP location (i.e., availability zone) and its ability for CSC. The soft requirements refer to performance, cost and support criteria. Upon the arrival of a new request for slice deployment (Step 2), the filtering mechanism realizes the first stage of the EPoP selection. It retrieves the advertised data of EPoPs from the Service Registry (Step 2) and creates the set of candidate EPoPs that satisfy the hard requirements of the network slice. Then, the Filtering Mechanism forwards this set to the PoP selection Mechanism for further processing (Step 4a).
- **PoP Ranking Mechanism**. The final PoP ranking and the selection of the most appropriate is performed by this component. The PoP Ranking mechanism retrieves information for the candidates EPoPs from the Service Registry (Step 4b). This information includes the advertised values of each EPoPs regarding the user's soft requirements. The ranking process is performed by the FAHP, which is a multi-criteria decision making method based on numeric and fuzzy KPIs. This component decides the EPoP, which will host the network slice, and the MANO component is notified for further actions (Step 5). In the following paragraphs, the details of FAHP are presented.

B. Ranking Criteria For Network Slicing

FAHP provides a hierarchical structure of criteria and attributes, which are used for the computation of the EPoPs ranking. The key difference between a KPI and an attribute is that the first express a specific technical or non-technical metric, while the second summarizes relevant KPIs. Toward the automated network slice deployment, we define various relevant KPIs, as those are show in Table I, which are also widely used in many cloud provider selection studies [9], [13]. Figure 2 shows an the hierarchical structure of our approach, which includes the most essential attributes and KPIs for the network slice case. This structure is intentionally kept as minimal as possible in order to easily present the details of FAHP. Nevertheless, it can easily extended in terms of attributes and KPIs. The numeric performance and cost KPIs are defined by CSMIC [17], while the fuzzy KPIs of support are defined in [12]. The EPoPs advertise their values for the defined numeric and fuzzy KPIs (Table I). For example, the *Service Availability* KPI has a numeric value (e.g. 95%), while the *Bandwidth* KPI is measured by range values. Regarding the fuzzy KPIs, i.e., *Technical Support*, linguistic terms (e.g. "HIGH") are used.

TABLE II
LINGUISTIC TERMS AND MEMBERSHIP FUNCTIONS OF FUZZY NUMBERS

Linguistic Term	Membership Function
Very Low (VL)	$(1,2,3)$
Low (L)	$(3,4,5)$
Medium (M)	$(4,5,6)$
High (H)	$(5,6,7)$
Very High (VH)	$(6,7,8)$
Excellent (E)	$(7,8,9)$

C. FAHP Phases

In the following, the phases of the proposed FAHP are described in detail.

Phase 1 - User's Requirements Definition Before proceeding to a Network Slice deployment request, the user assigns weights on the attributes that express its hard and soft requirements. As it mentioned earlier, the hard constraints are processed by the filtering mechanism. After that, the candidate EPoPs will be ranked from the EPoP ranking mechanism based on FAHP. The user's requirements correspond to the importance of each attribute in the hierarchical structure. In essence, this is a weight assignment. As it shown in Figure 2 each edge between two nodes has a weight, that reflects the importance of the lower level attribute or KPI on the computation of the upper level attribute's value. We assume that the weight of the attribute or KPI j at level i, $w_{ij} \leq 1$, and the sum of weights of a group of siblings attributes or KPIs of an attribute j at level i, $\sum w_{ij}$ is equal to 1. In order to avoid meaningless weight assignment, the Consistency Ratio (CR) [18] is calculated for each group of siblings attributes.

Phase 2 - Relative Attribute Importance Computation The candidate for selection EPoPs, are evaluated by the PoP Ranking Mechanism of the EPSF. For each candidate EPoP, the advertised data in the Service Registry are used for computing the Relative Comparison Matrix (RCM). Assuming that n EPoPs take place in the ranking procedure and A_i, where $i = 1, 2, ..., n$ is the value that is advertised from the EPoP i for the KPI X. Then the RCM of the KPI X is,

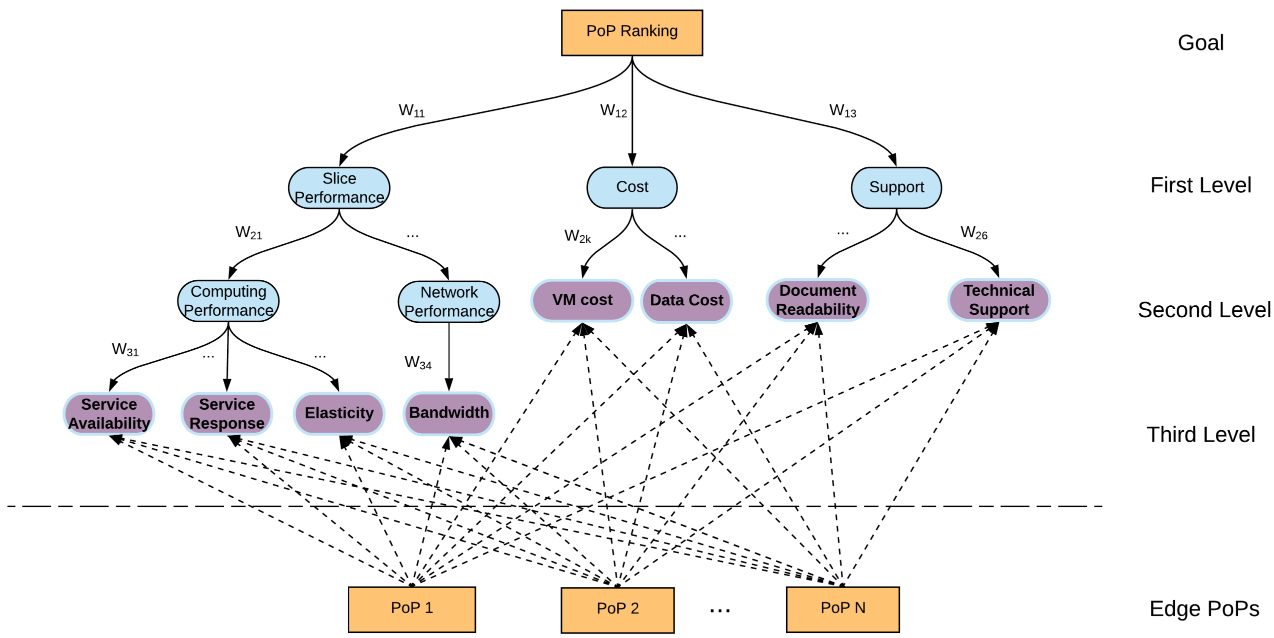

Fig. 2. Hierarchical Model for Edge PoP Selection

$$RCM_X = \begin{bmatrix} 1 & A_1/A_2 & \dots & A_1/A_n \\ A_2/A_1 & 1 & \dots & A_2/A_n \\ \vdots & \vdots & & \vdots \\ A_n/A_1 & A_n/A_2 & \dots & 1 \end{bmatrix} \quad (1)$$

There are KPIs of different types, so the necessary calculations are used for each different case. In the case of numeric KPIs, the extended AHP method is applied, as it is shown in SMICloud [10]. In the case of fuzzy KPIs, the fuzzy AHP approach is adopted according to the approach in [11]. For fuzzy systems, the interesting reader can refer to [19]. These methodologies use the RCM of each KPI at any level of the hierarchical structure according to the case, in order to calculate the Relative Ranking Vector (RRV) for every attribute of the hierarchy. At next, we present the steps of the calculations in the case of a fuzzy KPI. For these calculations, the linguistic terms are mapped onto triangular fuzzy numbers according to the Table II, and the respective fuzzy mathematical operations are used [11]. Let the N-dimension fuzzy $RCM_X = [x_{ij}]$, $i, j = 1, \dots, N$, the fuzzy synthetic extent is defined by,

$$D_i = \left(D_i^l, D_i^m, D_i^u\right) = \sum_{j=1}^{N} x_{ij} \otimes \left(\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ij}\right)^{-1} \quad (2)$$

We identify the attribute with the higher fuzzy synthetic degree by computing the degree of possibility for a fuzzy number i to be greater than a fuzzy number j,

$$V\left(D_i \geq D_j\right) = hgt\left(D_i \cap D_j\right) =$$
$$= \begin{cases} 1 & \text{if } D_i^m \geq D_j^m \\ \frac{D_j^l - D_i^u}{\left(D_i^m - D_i^u\right) - \left(D_j^m - D_j^l\right)} & \text{if } D_i^m \leq D_j^m \text{ and } D_j^l \leq D_i^u \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

The degree of possibility that a fuzzy synthetic extent D_i is greater than the rest synthetic fuzzy extents of the fuzzy RCM is,

$$d_i = V\left(D_i \geq D_k, \forall k = 1, \dots, N, k \neq i\right) = \min V\left(D_i \geq D_j\right) \quad (4)$$

Finally the normalized comparison vector is obtained,

$$RRV = \left[r_1 \dots r_N\right]^\top \text{ where } r_i = \frac{d_i}{\sum_{k=1}^{N} d_k} \quad (5)$$

Phase 3 - EPoPs Ranking and Decision After the computation of the RRV for each KPI, the same vector should be calculated for every attribute in the hierarchical structure. The assigned weights, as those defined in Phase 1, will be used in order to calculate the upper level $RRVs$.

Assuming n EPoPs, a parent attribute with m sub-attributes and the weight vector with m elements, the relative ranking vector of the parent attribute is defined,

$$RRV_{par} = \begin{bmatrix} r_{sub1}^1 & \dots & r_{subm}^1 \\ r_{sub1}^2 & \dots & r_{subm}^2 \\ \vdots & & \vdots \\ r_{sub1}^n & \dots & r_{subm}^n \end{bmatrix} \begin{bmatrix} w_{sub1} \\ \vdots \\ w_{subm} \end{bmatrix} = \begin{bmatrix} r_{par}^1 \\ \vdots \\ r_{par}^n \end{bmatrix} \quad (6)$$

TABLE III
ADVERTISED DATA FOR POP RANKING MECHANISM

Top Level	First Level	Second Level	Third Level	EPoP1 Data	EPoP2 Data	EPoP3 Data
PoP Ranking	Slice Performance (0.5)	Computing Performance (0.6)	Service Availability (0.4)	75%	81%	90%
			Service Response (0.3)	135	50	143
			Elasticity (0.3)	3	2	1
		Network Performance (0.4)	Bandwidth (1.0)	10	40	20
	Cost (0.2)	VM Cost (0.6)	-	11	16	32
		Data Cost (0.4)	-	0.06	0.094	0.095
	Support (0.3)	Document Readability (0.7)	-	[VH]	[M]	[L]
		Technical Support (0.3)	-	[M]	[H]	[H]

This bottom-up procedure leads to the top level RRV, which contains the final ranking result for the EPoPs.

IV. EPSF EVALUATION

This section evaluates the effectiveness of the EPSF. The following subsection demonstrates the steps of the EPSF and the computations of the FAHP. Then, an analysis of the results is discussed and the benefits of the multi-criteria decision making approach are illustrated. In our scenario, fifteen candidate EPoPs are available for network slice deployment. Each EPoP resides in one, of the five availability zone, which is actually the location of the edge infrastructure. The availability zone will be used as one of the hard constraints for the filtering mechanism, besides with the CSC capability. Table III shows the input for the ranking mechanism, as it turns out from the EPoPs advertised data in Service Registry and the user's requirements for the corresponding KPIs and attributes.

A. EPSF Ranking Mechanism - A Numerical Example

In this experimental setting, the user defines the hard requirements about the EPoPs as input in the EPSF's Filtering Mechanism. The user's hard requirements are $Availability\ Zone = [zone1,\ zone3,\ zone5]$ and $Cross-Slice\ Communication\ =\ "Enabled"$. After the filtering procedure, three candidates EPoPs are forwarded to the PoP Ranking Mechanism, as shown in Table III. The PoP Ranking Mechanism follows the bottom-up FAHP. For example, we present the RRV calculation for the fuzzy KPI of Document Readability. According to the input from Table III, the fuzzy RCM for this KPI is,

$$RCM_{docR} = \begin{bmatrix} (1,1,1) & (1,\ 1.4,\ 2) & (1.2,\ 1.75,\ 2.67) \\ (0.5,\ 0.71,\ 1) & (1,1,1) & (0.8,\ 1.25,\ 2) \\ (0.38,\ 0.57,\ 0.83) & (0.5,\ 0.8,\ 1.25) & (1,1,1) \end{bmatrix}$$

Then, the fuzzy synthetic extent is computed for each EPoP according to $RCM_{DocRead}$ and (2),

$$D_1 = (0.25, 0.437, 0.768)$$
$$D_2 = (0.18, 0.31, 0.54)$$
$$D_3 = (0.147, 0.25, 0.418)$$

The degree of possibility that a fuzzy synthetic extent D_i is greater than the rest synthetic fuzzy extents of the fuzzy RCM for Document Readability according to (3) and (4) is,

$$d_1 = 1,\ d_2 = 0.699\ and\ d_3 = 0.471$$

According to (5), we calculate the relative ranking vector for the Document Readability,

$$RRV_{docR} = [0.46\ 0.32\ 0.22]^\top$$

Following the same procedure for the "Technical Support" KPI we calculate the corresponding RRV,

$$RRV_{tecS} = [0.288\ 0.356\ 0.356]^\top$$

According to the Phase 2 of the PoP Ranking Mechanism, we obtain the RRV of the "Support" attribute. In this procedure the assigned weights of the siblings KPIs will be used,

$$RRV_{sup} = \begin{bmatrix} 0.46 & 0.288 \\ 0.32 & 0.356 \\ 0.22 & 0.356 \end{bmatrix} \begin{bmatrix} 0.7 \\ 0.3 \end{bmatrix} = \begin{bmatrix} 0.41 \\ 0.33 \\ 0.26 \end{bmatrix}$$

Following the same procedure for the rest of the attributes, but using the calculation for the numeric type, the respective RRV for each one is,

$$RRV_{comPer} = [0.336\ 0.406\ 0.257]^\top$$
$$RRV_{netPer} = [0.142\ 0.571\ 0.285]^\top$$
$$RRV_{sliPer} = [0.259\ 0.472\ 0.268]^\top$$
$$RRV_{cost} = [0.471\ 0.315\ 0.212]^\top$$

The overall Ranking for the candidate EPoPs is calculated,

$$RRV_{overall} = \begin{bmatrix} 0.259 & 0.471 & 0.41 \\ 0.472 & 0.315 & 0.33 \\ 0.268 & 0.212 & 0.26 \end{bmatrix} \begin{bmatrix} 0.5 \\ 0.2 \\ 0.3 \end{bmatrix} = \begin{bmatrix} 0.346 \\ 0.398 \\ 0.254 \end{bmatrix}$$

So, according to the user's requirements and the advertised to the Service Registry Data, the EPoPs ranking from the best to the worst is: $(1)EPoP2$, $(2)EPoP1$, $(3)EPoP3$.

B. Result Analysis and EPSF Scalability

From the above example, the following remarks can be made about the importance of each component of the EPSF. The Filtering Mechanism provides an initial coarse separation based on the location and CSC criteria. Especially the CSC criteria is essential for guaranteeing the performance of a network slice and the optimal resource allocation of the EPoPs.

The following example illustrates the importance of the CSC-based filtering. Without the Filtering Mechanism, all EPoPs are evaluated by the multi-criteria ranking mechanism. However, the deployment and the performance of a network slice depend heavily on the location and CSC criteria. We assume that $EPoP_x$ meet both criteria, while $EPoP_y$ does not satisfy any of them. Furthermore, we assume that the generated external network traffic for the basic functionalities of the network slice is 100 data units and the network slice requires communication with already deployed network slices. Under this setting, the deployment of the network slice in CSC-enabled $EPoP_x$ creates only intra-PoP traffic without any additionally cost. On the contrary, if the network slice is deployed in $EPoP_y$, the network slice should either allocate extra resources to deploy the external required services or generate extra inter-PoP network traffic, which increases the overall deployment cost.

The next remark is related to the necessity of a multi-criteria decision making methodology. Initially, the proposed Ranking Mechanism allows the user to adjust the weights of the KPIs according to its slice requirements. Secondly, it is obvious that the initial filtering is necessary but cannot guarantee the optimal selection by itself. Considering the example of the previous section, we demonstrate the selection of the suitable EPoP based on a single objective, e.g., the *Cost* attribute. As it is shown below, by feeding the FAHP with the corresponding data of Table III, the selected EPoP would be the EPoP1, as it has the highest ranking and is the lowest-price solution.

$$RRV_{cost} = [0.471\ 0.315\ 0.212]^{\top}$$

However, the ranking of the multi-criteria FAHP was different and EPoP2 was selected for the deployment of the network slice.

$$RRV_{overall} = [0.346\ 0.398\ 0.254]^{\top}$$

Both remarks show that the two-stages of the EPSF are essential to include all the dominant parameters of selecting the appropriate PoP for the slice deployment. Finally, it is worth noting that the EPSF is scalable in terms of KPIs, attributes and candidate PoPs. The FAHP algorithm, on which the PoP Ranking Mechanism is based, has low complexity, as the relative ranking vectors an any level of the hierarchical structure are computed by simple mathematical formulas.

V. Conclusions and Future Work

This paper presents a multi-criteria decision framework for selecting the most suitable Edge PoP in order to deploy a network slice. The Edge PoP Selecting Framework consists of three main components: (1) the Service Registry, which contains the necessary values of KPIs for each candidate EPoP, (2) the Filtering Mechanism, which performs a initial coarsing filtering of the candidate EPoPs based on user's hard requirements and (3) the PoP Ranking Mechanism, which is based on multi-criteria FAHP method and selects the most appropriate EPoP for the slice deployment. The overall performance of the proposed EPSF is evaluated under a realistic scenario and compared with simple filtering and a single-object FAHP approach. The results show that the two-stage framework is essential to meet the hard and soft user's requirements and enable the cross-slice communication and optimal resource allocation from the provider's perspective.

Our future work will focus on implementing a distributed PoP selection mechanism, which will facilitate both service discovery and cross slice communication. In this case, each edge PoP will maintain its service catalogue that will contain enriched information for the EPoP's KPI and the already deployed slices. Under this setting, the slice owner will be able to decide where to deploy his slice and with which deployed slice can establish cross slice communication in order to further reduce the deployment cost.

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