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Slice-aware resource orchestration of an elastic 5G network via evolutionary algorithms

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***Abstract*—Fifth generation mobile networks (5G) will enable new use cases for industries and vertical markets via numerous innovative approaches that overcome limitations of existing systems. Two concepts essential for the realization of 5G, are network elasticity and slicing. The application of these concepts allows the simultaneous hosting of more services that use a common resource pool while reducing operation and capital expenses. The realization of these benefits demands an efficient method to scale the resources allocated between different slices often with diverse demands. We apply a multi-objective approach, based on evolutionary algorithms to accomplish optimized resource orchestration between cloud-based slices in a 5G network deployed over a large European city. Numerical results are provided for the proposed approach and are compared to other allocation schemes.**

I. Introduction

5G networks promise to support higher speeds, a vast increase of connected devices, denser networks, enhanced connectivity even in high speed mobility scenarios, while offering lower latency services and energy consumption compared to current generation networks. They are expected to be commercially deployed by 2020, enabling new and diverse use cases and services to an extensive range of industries and vertical markets [1].

These use cases can be clustered into three broad categories, based on their demands and characteristics [1], [2]: Services belonging to the enhanced Mobile Broadband (eMBB) category will require very high data rates and seamless coverage. Examples of eMBB services include virtual or augmented reality applications (VR/AR) and streaming ultra high definition (UHD) video. The second service type, is ultra-Reliable and Low Latency Communications (URLLC) also reffered as mission-critical communications which require very high reliability combined with very low latency. Use cases include self-driving vehicles, remote operation of heavy machinery or industrial automation while some of these applications. Services belonging in this category might also require high data rates, for example performance of remote surgery. Finally massive Machine Type Communications (mMTC) will supports dense communications with small packet size and low throughput by massive amount of Internet of Things (IoT) devices e.g. use cases such as sensors monitoring environmental pollution in a smart city environment or sensors used for smart shipment tracking.

Through the research backed by various public and private organizations and partnerships and the effort of standards development organizations (SDOs), numerous concepts have been established as the basis used to tackle the technical and service requirements of 5G networks, e.g use of massive MIMO antenna arrays for the radio frequency (RF) 5G interfaces or the cloudification of radio access network (RAN).

Two innovations that are foundational for the realization of 5G networks, are virtualized network functions (VNF) and network slicing [3], [4]. Network function virtualization, aims to the creation of networks functions that can be deployed in general purpose hardware instead of using specialized hardware, as was the case in legacy networks. These functions can then be hosted in virtual machines or software containers sharing common computation, storage or network resources. The concept of network slicing, concerns a network architecture that enables the network to create slices on a common physical infrastructure that essentially are multiple, parallel independent end-to-end (E2E) logical networks covering the entirety of the network domains (core, transport and radio access networks). Each network slice instance (NSI) contains all functionalities and resources required to support the use case it was designed to serve [5].

The combination of these concepts will allow multi-tenancy and on-demand service and resource provisioning [6]. This aspect of a 5G system refers to the network ability to adapt load fluctuations as and when required efficiently matching the resources available with the demand is termed as network resource elasticity. 5G systems are elastic in three different dimensions: Operations that concern adapting the size of the VNFs to preserve their performance are referred to as Computational Elasticity while flexibly placing and chaining the various VNFs in an efficient manner is Orchestration-driven lasticity. The final dimension is Slice-aware or Cross Slice elasticity which leverages multiplexing gains by upscaling and downscaling network slice sizes as required. Employing cross-slice resource provisioning mechanisms, allows hosting more slices in the same infrastructure or serving the existing ones in a more efficient manner compared to networks without this mechanism [4].

The rest of the paper is organized as follows. In section II we review relevant works from the available literature, while in section III we briefly describe of evolutionary algorithms and present a cursory overview of our contributions. In section IV we present and formulate the resource allocation problem , whereas section V contains the setup of our simulation along with the numerical results of the approach we suggest in comparison with other methods.

II. Related Works and key contributions

Most real-world optimization problems have multiple objectives which are sometime conflicting. To address this class of problems, various multi-objective optimization (MOOP) methods that can simultaneously handle multiple objective functions have been developed. These methods have produced efficient solutions for problems in fields ranging from engineering and medicine to economics [7], [8]. MOOP approaches have been used in the context of 5G networks to handle problems concerning network dimensioning [9], optimization of network energy use [10], and computational and orchestration driven elasticity [11]–[14] or the orchestration of networks without elasticity [15], [16].

While these results indicate that the problem of cross-slice resource allocation in a 5G system can be effectively handled by using MOOP techniques, existing approaches are based single or double-objectives e.g. [3] and cases of more objectives are solved in stages [18]. Another gap in the existing literature, is the method of handling the allocation of the computational resources used by the virtual machines hosting the VNFs. Existing research focuses in the optimization of throughput, Signal-to-Interference-plus-Noise-Ratio, physical resource blocks (PRBs) i.e. radio resources while not taking into account resources such as CPU, Memory etc. A theoretical model that describes computational resource allocation in 5G network is available in [19]. Finally, another benefit gained by using multi-objective algorithms is that in contrast with tools from game theory , e.g. [17], no prior assumptions such as loss/revenue margins or user network traffic patterns are required.

In our study we implemented a resource allocation method for the different slices with diverse resource demands of a 5G system. To the best of our knowledge, an approach that uses MO evolutionary algorithms to optimize the resources shared between slices has not been yet examined.

Using a multi-objective optimization approach we propose a scheme that takes into account both the virtualized and the radio parts of the network and produces multiple solutions that can represent optimal decisions for the inter-slice resource orchestration based on various trade-offs for the various metrics used to evaluate the network performance. Additionally, the method is easily extendable in terms of resource types and objective functions modeled.

III. Evolutionary algorithms

Evolutionary algorithms are a subset of evolutionary computation. Along with other techniques and methods such as artificial neural networks, fuzzy logic or swarm intelligence they belong to the Computational Intelligence field of study, also known as soft computing, a sub-discipline of the Artificial Intelligence field. These approaches can easily adapt to changes of the input data, effectively represent numerical knowledge and efficiently produce solutions in computationally hard problems using robust approximation models [20].

The basic process of an evolutionary algorithms involves the evolution of a population that represents a set of solutions using predefined objective functions. The optimization process is iterative and such each iteration is called a generation. In each generation a number of operators called genetic or evolutionary are applied to the population to evolve it towards optimized solutions. A detailed description of various MOOP related methods is available in [7]. Since the objective functions of a MO problem can often be conflicting, improving the value of one can cause the deterioration of the results of one or more of the rest of the objective functions. Such a problem has no unique optimal solution, instead the solution is a set consisting optimal trade-off solutions, called Pareto-optimal. These solutions are said to be non-dominated i.e. for each of them the improvement of any objective function value comes at the expense of one or more objective function results.

In our experiments we use the Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [21]. Decomposition using weights is a classic method for solving MOOP: the weights represent the significance of the objectives and are used to transform the initial problem to one with a single objective. Utilizing decomposition, MOEA/D finds optimal solutions for each objective and then based on these solutions uses operators to evolve the initial population. Decomposition can be performed by other methods than weighting such as the Tchebyscheff scalarization method [21].

IV. Proposed Model

The purpose of our model is to optimize a number of slices $S = \{s_1, .., s_i\}$, during a number of time points $T = \{t_1, .., t_{|T|}\}$. Each slice has a number of user requests $U_{qs_i} = \{u_{1s_i}, u_{2s_i}, ..., u_{|U|s_i}\}$. At any given time point t_k we denote as $D_{s_i}^{t_k} = [u_m, ..., u_n]$ the ordered set of requests at the waiting list of a slice s_i.

Each network slice instance corresponds to a service offered by the network, e.g., a virtual reality (VR) application or mobile browsing. The total demand per slice is defined as follows. Given the set of slices $S = \{s_1, .., s_i\}$, the set of time periods $T = \{t_1, .., t_{|T|}\}$, and the set of user service requests $U_{qs_i} = \{u_{1s_i}, u_{2s_i}, ..., u_{|U|s_i}\}$, define as $D_{s_i}^{t_k}$ the vector that represents the list of requests that wait in the execution queue of slice s_i at time t_k. Next, we need to define the resources needed to serve the requests for the slices $E = \{e_{1s_{|S|}}, e_{2s_{|S|}}, ..., e_{|E|s_{|S|}}\}$. E is a subset of the set P describing the entire network resource pool, $E \subseteq P$.

The objective functions $Obj_j = \{Obj_1, .., Obj_{|J|}\}$ form the basis of the evolutionary algorithms which in the case of the 5G networks can be KPIs such as user data rate or resource utilization.

The desired result of the algorithm is the definition of a mapping function $f : P \times D_{s_j}^{t_i} \mathcal{P}(P)$, for all $t_i \in T, s_j \in S$, and $\mathcal{P}(P)$ which is the power set of P.

In other words, given the demand $D_{s_j}^{t_i}$ and the available resources P, function f returns a list of resources allocated to slice s_j at time t_i, while also minimizing the list of objectives J.

The final decision on resource allocation is done by using the evolutionary algorithm to minimize the following:

$$\arg min_f \text{ J(f)}$$

subject to $Obj_j^{min} \leqslant Obj_j \leqslant Obj_j^{max}$

Forming the problem in such a manner, allows adding additional bounds based on service level agreements (SLA), e.g. a slice hosting a virtual reality application might require high data rates to function but allocation of resource amounts higher than needed raises the operational costs for the MNO. In this scenario, adding throughput as objective would lead to the following constraint:
$Obj_{throughput}^{min}(s_i) \leqslant Obj_{throughput}(s_i) \leqslant Obj_{throughput}^{max}(s_i)$. Additional constraints can easily be added based on different scenarios and needs of network use.

A. Application of the proposed model

The model proposed in the previous section, is used to simulate a resource allocation problem in a network with slice-aware elasticity enabled, where some the base stations face traffic congestion. The binary function $X_{S_{ij}}$ is used to describe the request admission result:

$$X_{U_j,S_i} = \begin{cases} 1, \text{if slice } S_i \text{ request } u_j \text{ can be served,} \\ 0, \text{if request cannot be served.} \end{cases}$$

Before the definition of the objective functions that will be used for the network optimization and the evaluation of its performance, the amount of the required resources and their cost for each network slice has to be determined. The demand of radio resources, throughput and power consumption per slice s_i for each cell is:

$$\text{Throughput demand per slice } s_i : e_{1S_i}(u_{js_i}) = \sum_1^j \text{Throughput demand} * x_{u_j,s_i}$$

$$\text{Power demand per slice } s_i : e_{2S_i}(u_{js_i}) = \sum_1^j \text{Power demand} * x_{u_j,s_i}$$

Concerning computational resource use per Cell, the CPU demand for slice s_i for each cell is:

$$e_{3S_i}(u_{js_i}) = \sum_1^j \text{CPU required} * x_{u_j,s_i}$$

And the summed total cost of the resources demanded per slice s_i is:

$$C_{S_i}(u_{js_i}) = \sum_1^j \text{Cost demanded resources} * x_{u_j,s_i}$$

The amount of network resources consumed by all slices is: a) Throughput consumption $e_{1_{tot}} = \sum_1^j e_{1_{S_j}}$, b) Cell power consumption $e_{2_{tot}} = \sum_1^j e_{2_{S_j}}$ and c) CPU consumption $e_{3_{tot}} = \sum_1^j e_{3_{S_j}}$.

The resource pool of the network i.e. maximum Throughput, Power and CPU amount available is P=(r_1, r_2,r_3). The objective functions can now be defined :
Total throughput consumed, Obj_1**:** *Total throughput consumed to service all accepted requests* : $\text{argmin}_{e_sS_i\in E} \sum_{i=1,j=1}^{i=n,j=m} \frac{x_{u_j,s_i} * e_{1S_{ij}}}{A}$

Mean throughput consumed by user, Obj_2**:** *Average throughput consumed by an accepted request*: $\text{argmin}_{e_sS_i\in E} \sum_{i=1,j=1}^{i=n,j=m} \frac{e_{1S_{ij}}}{n}$

Cost efficiency, Obj_3**:** *average cost of accepted requests*: $min \sum_{i=1,j=1}^{i=n,j=m} \frac{C_{S_{ij}}}{n}$

Resource utilization, Obj_4**:** *Total resources allocated as a fraction of all available resources:*
$\text{argmax}_{e_sS_i\in E} \sum_{i=1,j=1}^{i=n,j=m} \frac{r_1}{e_{1_{tot}}} + \frac{r_2}{e_{2_{tot}}} + \frac{r_3}{e_{3_{tot}}}$
The process of minimizing the KPI values is subject to a number of constrains. It follows reason that resource consumption cannot exceed available resources:
$e_{1tot} \leqslant r_1$, $e_{2tot} \leqslant r_2$, $e_{3tot} \leqslant r_3$.
Using the constrains and the objective functions given above, the following problem can be solved by the MOEA/D algorithm: argmin_f J $= \text{argmin}_f[-obj_1, -obj_2, obj_3, -obj_4]$.

The step-by-step outline of the process used for the multi-objective optimization based resource allocation is given in Algorithm 1.

Algorithm 1 Pseudo-Code for slice-aware resource allocation using multi-objective optimization

1: **Initialization:**
   $\forall$ cell , $\forall$ slice:
   - Determine available resource pool, number of traffic requests and aggregate resource demand
2: Problem formulation:
   - Define objective functions and constrains
   - Set population size and number of generations
3: **Optimization using MOEA/D**:
   - Generate starting random population
   - Calculate reference point for the Tchebyscheff decomposition
   - Evaluate the values of objective function
   - Evolve population using genetic operators and calculate new objective functions
   - Repair population, taking into account any constraint violations
   - Update population with evolved solution
4: **While** iteration $\leq$ generations size:
   - repeat **step 3**
5: Perform selection from the Pareto solution set and allocate resources
6: **If** number of traffic requests served $<$ number of traffic requests served:
   - determine number of requests not served
   - assign requests to closest cell with resources available
   - Go to step 1

V. Performance Evaluation

A. Experiment setup

o test the proposed approach, a network s situated in the Hamburg city and Port with 85 sites microsites with 1 remote radio heads(RRH) per site and 7 Macro-sites with 3 RRH was simulated, shown in figure 1. The data concerning traffic distribution, throughput and CPU requirements was produced using the Mx-Art network level simulator [22]. The methodology for the calculation of CPU requirements of each

Fig. 1. Map of base station locations used in the simulation. Blue dots show the macro-sites and red the micro-sites.

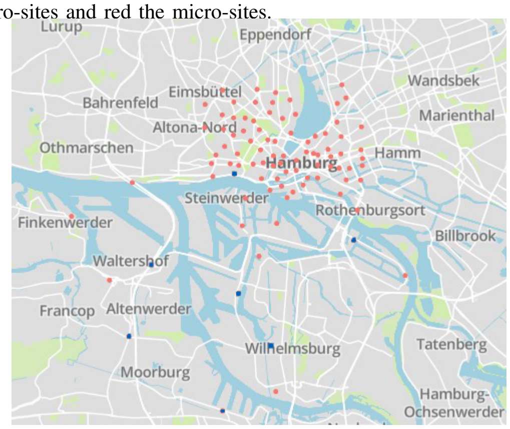


TABLE I. ASSUMPTIONS USED IN THE SIMULATION

Simulation Parameters
Antenna system : Single-Input, Single-Output (SISO)
Bandwidth capacity per cell: 20 MHz
Modulation: 64QAM, **Modulation scheme (MCS)** : 18, **TBS Index**: 26
Cost per GB: 72.34 €, **Max Throughput per cell**: 75.376 Mbps
Max CPU per cell: 10 CPUs, **Max Power per cell**: 120 kW
Simulation Duration: 230 time points with duration of 100 s
For each slice, min,max,mean number of requests per cell and mean Throughput per request :
URLLC Slice : [2,180,36,0.528], **eMBB Slice** : [2,18, 11, 5.167]
IoT Slice : [3,137,21,0.4428]

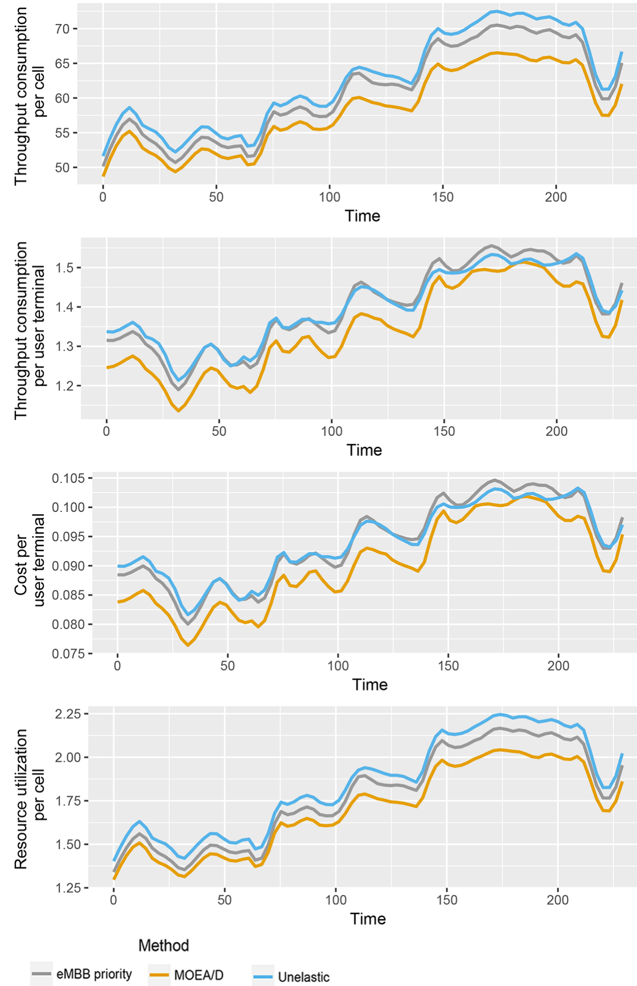
service can be found in [23]. Power consumption of the cells was computed using the models proposed in [24]. The average cost per GB was calculated using the Capische analytical tool [25]. Various assumptions used in the simulation are available in V-A The simulation uses the *PYGMO 2* [26] optimization toolbox and was performed using Python.

The scenario assumes three slice types: an eMBB service with high resource demands, an URLLC with a lower resource demands and an IoT slice with the lowest resource demand.Traffic requests are gradually increased to a peak in the period between time points 140 and 220.

To simplify the process, we presume no interference, no path loss propagation etc. when a request is redirected to another cell. To offset for these simplifications we impose a penalty in all cases where a request cannot be served by the cell it was originally made. If a request originally required $e_{r\_original}$ radio resources (Throughput, Power), it needs $e_{r\_updated} = e_{r\_original} + 0.2 * d * e_{r\_original}$ if it is served by another cell with distance d from the original cell.

In order to better showcase our results, results for four additional allocation schemes where produced: a) A scheme that uses the proposed method but employs the NSGA-II algorithm,commonly used as a benchmark in MOOP problems [27] b) a case where we assume that there is the network is not elastic and the resource allocation is fixed (eMBB slice: 60%, URLLC slice: 30% and IoT slice: 10% of total available resources) c) a scheme where the most resource-demanding user requests have priority i.e first eMBB requests are served then URLLC requests and finally IoT and d) a scheme where the least resource-demanding user requests have priority (IoT then URLLC and lastly eMBB).

Fig. 2. Averaged values of the objective functions throughout the simulation (lines smoothed using LOESS with smoothing parameter a=0.1).



A population size of 36 was used for the MOEA/D algorithm and a population size of 35 for the NSGA-II algorithm. Both populations where evolved for 300 generations.

B. Simulation results

MO algorithms produce a set of trade-off solutions as discussed in section III. The values of the Pareto set were decomposed using decomposition with equivalent weights (w = 0.2) to select a solution that is equally balanced for all objective functions.

As shown in table II, the solution that uses the MOEA/D requires on average less resources and has less cost while serving the same number of requests compared to the other allocation schemes. The NSGA-II benchmark method performs very close to the proposed solution, with the objective functions results being approximately 1% less than those of the the MOEA/D method. The results of the best performing naive scheme i.e. the one prioritizing the eMBB slice requests, are between 4% to 5% less than the MOEA/D solutions.

To showcase the performance of the proposed scheme its' results are plotted, along with the results of the two best performing naive methods, Unelastic and eMBB-priority:

TABLE II. AVERAGED EVALUATION RESULTS FOR THE DIFFERENT RESOURCE ALLOCATION METHOD.

Method \ Metric	Throughput per Cell	Throughput per user request	Resource Utilization	Cost
MOEA/D	**71.2343**	**1.3421**	**1.7023**	**0.0903**
NSGA-2	71.6286	1.3533	1.7193	0.0910
eMBB priority	73.25592	1.3989	1.7829	0.094
IoT priority	73.22250	2.1724	1.7833	0.1134
Unelastic network	74.43534	1.3993	1.8493	0.0941

The MOEA/D method steadily outperforms both of the naive methods throughout the simulation period, as shown in figure 2. It should be also noted that in the peak traffic period the average cost of the scheme that prioritizes the eMBB slice is larger that the cost of the unelastic scheme.

VI. CONCLUSIONS

In this paper,a resource allocation method between network slices is proposed, based on multi-objective optimization and implemented on a 5G network. The simulations show that the method proposed produces better results compared to another MO algorithm and three naive resource allocation schemes, serving the same number of user requests with a lower cost and resource consumption. As follow-up work, we intent to further develop our approach, so it uses variable modulation schemes and propagation path loss models. We plan to experiment with in scenarios that involve more slices with different owners, taking into account cell switch off to achieve further operational cost reduction and using more evaluation metrics, especially metrics related to latency.

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