Dynamic Selection of User Plane Function in 5G Environments

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***Abstract*— This paper studies the optimal User Plane Function (UPF) selection problem in 5G environments. UPF functionality is performed through programmable optical network nodes. Dynamic selection of UPF processing minimizing the overall service delay is performed through a novel Evolutionary Game Theory model.**

Keywords—5G, Evolutionary Game Theory, MEC, UPF

I. Introduction

5G communication systems rely on an open and flexible network paradigm to address the requirements of both telecom operators and vertical stakeholders in a cost and energy efficient manner. To achieve this, the concepts of hardware programmability and network softwarisation are adopted to develop suitable interfaces that can be used to a) interconnect a variety of wired and wireless network technologies forming a common transport network (TN) and, b) decouple Control and User plane (CP-UP) functionalities. The former facilitates implementation of a variety of 5G-Radio Access Network (RAN) deployment options, while CP-UP separation (CUPS) allows flexibility in network deployment and operation as well as cost efficient traffic management.

A big part of the user plane functionality in 5G systems is handled by the User Plane Function (UPF), which has to be designed to support challenging 5G services with very tight performance requirements. It connects with external IP networks hiding mobility related aspects from the external networks. Moreover, it performs different types of processing of the forwarded data, such as packet inspection, redirection of traffic and application of different data rate limitations. 5G-CUPS supporting multiple UPFs enables 5G edge capabilities; one of the key 5G advancements compared to 4G. UPF related processing can be dynamically deployed and configured depending on the applications' needs. Overall, UPFs act as termination points for various interfaces and protocols and are also responsible to take several actions (rules) [1] including: (a) Mapping of traffic to the appropriate tunnels based on the QoS Flow Identifier (QFI) information. This requires UPFs to be able to perform Deep Packet Inspection and identify the necessary values in the General Packet Radio Service Tunnelling Protocol (GTP-U) header, associate QFIs with the appropriate Differentiated Services Code Point (DSCP) codes in the external IP network and perform the relevant protocol adaptations at line rate. (b) Steering of packets to the appropriate output port and take the necessary packet forwarding actions. (c) Packet counting for charging and policy control purposes. (d) Deep packet inspection for security and anomaly detection purposes. (e) Buffering and queuing management for traffic service differentiation and assurance of end-to-end delays.

To perform these actions UPFs should support an extensive set of protocols such as, GTP-U, PFCP (Packet Forward Control Packet), IP and also assist in the operation of SDAP (Service Data Adaptation Protocol) and PDCP (Packet Data Convergence Protocol) through mapping of DSCP classified IP traffic coming from the external Data Networks (DN). It should be also capable of handling legacy and new protocols such as enhanced CPRI/Open RAN and Radio over Ethernet (RoE) at high-rates. Towards this direction, *programmable optical networks (*e.g. Time Shared Optical Network-TSON [5]) can be effectively used to support transport network requirements as well as classify and steer traffic. This is performed adopting specific interfaces for control plane (N1/2, N4), user plane (N3, N6) and UPF handover (N9) communication requirements. For example, the Network Interface Cards (NICs) can steer control plane protocols packets such as PFCP packets into the Session Management Function (SMF) or the control plane part of UPF and can steer User Equipment (UE) sessions based on the PDU session, the flow, the QoS class etc. through N3 and N6 interfaces. Programming can be also used to support extended header (EH) for 5G user plane traffic.

A high-level view of a 5G deployment option adopting Fronthaul and Backhaul Transport Nodes (FTN/BTN) and multiple UPFs supporting the disaggregated 5G-RAN approach is shown in Fig. 1. In this figure the Remote Unit (RU), the Distributed Unit (DU) and the Central Unit (CU) can be either collocated or located separately adopting either a Mobile Edge Computing (MEC) or a Central Cloud (CC) architectural approach. Based on the 5G-RAN deployment option and the type of service that needs to be provided, UPF nodes can be placed closer or further away from the 5G-RAN. In this context, as the network dimension grows, a larger number of rules is required to support policies, whereas network resources (e.g., switch memory) are limited. This may result in increased service delay as the number of flows requiring UPF processing increase.

To address this problem, we propose a novel scheme based on Evolutionary Game Theory (EGT) that allows dynamic selection of the optimal UPF elements. So far, a very limited set of studies exist addressing the problem of UPF selection [2]. The present study formulates the optimal UPF selection problem considering a specific optical node implementation [5] and using accurate modeling of the delays introduced when this programmable optical node is adopted to act as UPF element as shown in Fig. 1.

II. Network Description and Problem Formulation

A. System Model

We consider the uplink transmission of a 5G network shown in Fig. 1. The UEs initiate the PDU Session Establishment pro-

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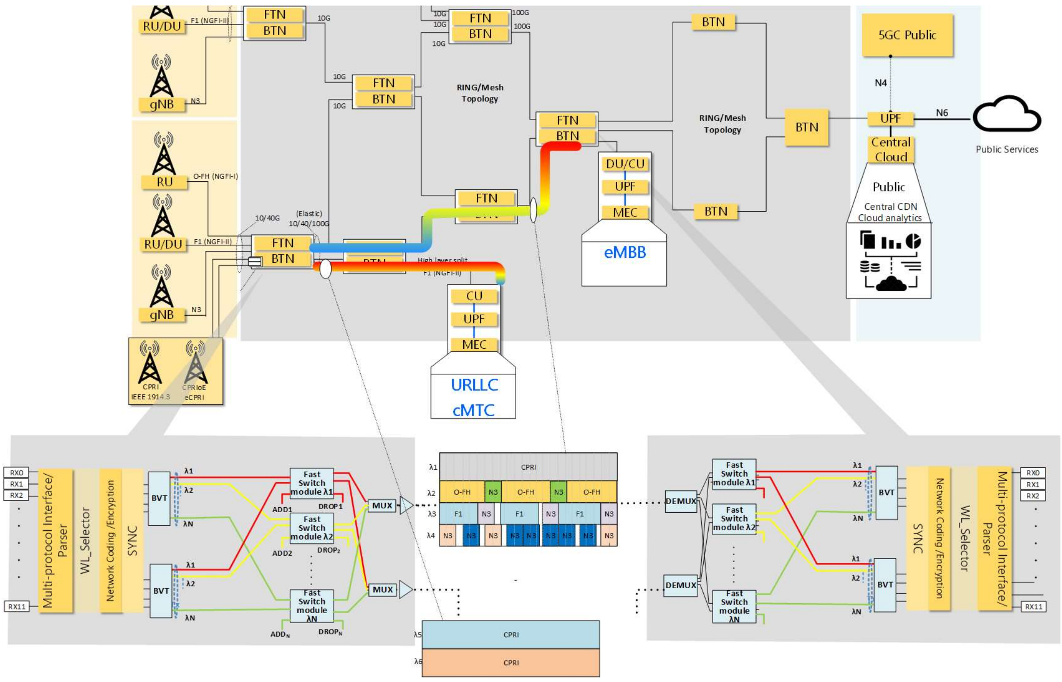


Fig. 1: 5G System architecture for access to two (e.g. local and central) data networks [3]

cess by transmitting the relevant request to the Access and Mobility Management Function (AMF). The AMF contacts the SMF, which in turn checks whether the UE requests are compliant with the user subscription. Once subscription information has been verified the SMF selects a UPF to serve the PDU Session. This is a key decision to be taken as a UPF at close proximity to the RAN, may be the optimal choice at first sight, since it should result in reduced latency. However, if all UEs are associated with this UPF congestion may arise resulting in increased latency. To address this challenge, we propose a scheme that allows dynamic selection of the UPFs by the UEs. In this approach users try to optimize their own performance selfishly. The choice adaptation process of the UEs can be formulated as an evolutionary game.

To formulate this problem, we consider a set of UEs each requesting a service of class $g \in G$ where G is the total number of available service classes. Let also $S^g = \{UPF_1^g, \dots, UPF_{N_g}^g\}$ be the set of available strategies in users belonging to g-group. For each group, each UE tunnel needs to be terminated at a specific UPF. Assuming that N_g denotes the available UPFs for group g, then the population of the UEs in group g can be described at each time instance by vector $\boldsymbol{x}^g(t) = [x_1^g(t) \dots x_{N_g}^g(t)]$ where $x_i^g(t)$ is the proportion of UEs in group g that are currently being served by UPF_i. Each UE belonging to a specific group remains associated with a UPF for a time interval, and reviews its choice periodically. When a revision occurs, the UE switches from UPF_i to another UPF_j according to a switching probability $p_{ij}^g(\boldsymbol{x}) = x_j^g$, that is equal to the population probability distribution of strategies, where $\boldsymbol{x} = [\boldsymbol{x}^1(t) \dots \boldsymbol{x}^g(t)]$, is the population state of the system. If a switch occurs, the UE receives a payoff $u_j^g(x)$ that quantifies its satisfaction level associated with the selection of UPF_j. The obtained payoff affects the arrival rate of the revision opportunities. Assuming that the number of reviews of a UE that uses strategy i can be described by a Poisson process with arrival rate $r_i^g(x)$, and all UEs' Poisson processes are statistically independent, we can use the law of large numbers to approximate the adaptation process with the following deterministic dynamic model [4]:

$$\dot{x}_i^g(t) = \sum_{j\in g} x_j^g(t) r_j^g(\boldsymbol{x}) p_{ji}^g(\boldsymbol{x}) - x_i^g(t) r_i^g(\boldsymbol{x}) \quad (1)$$

The UE updates its review rate, by linearly decreasing it to its current payoff. This means that the average review rate of a UE that uses strategy i is:

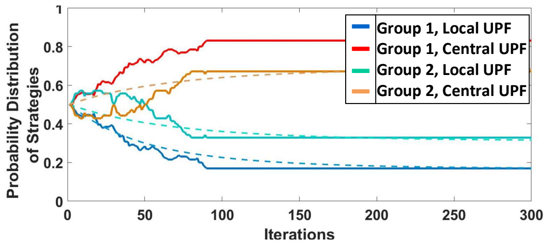
$$r_i^g(x) = \alpha - \beta u_j^g(\boldsymbol{x}), \quad \beta > 0 \ and \ \frac{\alpha}{\beta} > u_j^g(\boldsymbol{x}) \quad (2)$$

This results in forcing UEs with higher payoffs to revise their UPF choice at lower rates than the rest, leading to the replicator dynamics:

$$\dot{x}_i^g(t) = \beta\left(u_i^g(\boldsymbol{x}) - \overline{u^g}(\boldsymbol{x})\right) x_i^g \quad (3)$$

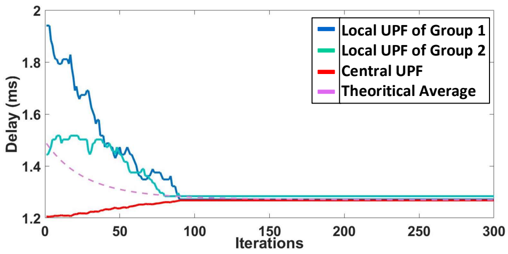
According to this equation, a selected strategy will either survive or be eliminated in the long run depending on whether its payoff is better or worse than the average payoff of all strategies. Since the objective of the UEs is to optimize their performance in terms of latency, greater payoffs correspond to lower delays.

The observed latency can be decomposed into two main components. The first component is the propagation delay between the UE and the UPF and is proportional to the distance between the two entities. Assuming an underlaying optical transport network, the propagation delay due to the propagation time in the fiber links corresponds to 5 μs per kilometer (km) of fiber. The second component is the delay of processing inside the UPF and can be modeled by adding the processing and the transmission delay, that are constant, and the variable queuing delay. Mechanisms for bounding the processing delay within a network node can be found both in literature and in standardization. In this analysis, we assumed that the UPF, uses the bounded mechanisms described in [3].



Full lines: simulation results, Dotted lines: theoretical results

a)



b)

Fig.2: (a) Trajectories of proportions of population and (b) convergence of the algorithm to the equilibrium (for $M_1 = 130, M_2 = 70, \frac{a}{b} = 1, \frac{k_{mec}}{k_{cc}} = 10$). In the equilibrium 16% of group1 UEs and 32% of group 2 UEs are served by their local UPFs, while the remaining are served by the central UPF.

Considering these we formulate the payoff on a user of group g that selects action i, when the population state is $\boldsymbol{x}(t)$, as

$$u_i^g(\boldsymbol{x}) = 1/t_{prop}{}_i^g + t_{UPF_i}(\boldsymbol{x}) \quad (4)$$

where t_{prop} is the propagation delay and $t_{UPF_i}(\boldsymbol{x})$ the UPF_i delay that can be approximated by an exponential function [5]:

$$t_{UPF_i}(\boldsymbol{x}) = e^{k_i \rho_{UE} \sum_{g=1}^{G} M_g x_i^g} \quad (5)$$

where ρ_{UE} is the traffic of one UE, M_g is the UE-population of group g and k_i is a variable related with UPF_i and depends on the characteristics of the UPF node implementation (Fig. 1) including data rate, number of ports (fibres, wavelengths), buffering capability etc.

B. *Application in 5G networks*

Based on the replicator dynamics of the EGT, we developed a scheme to attain the evolutionary equilibrium. The following steps summarize the algorithm : (1) *Initialization*: Every UE in each group chooses a strategy at random and observes its payoff u. Then it calculates its review rate λ according to the formula $\lambda = a - \beta u$, where α, β are constants. (2) Revision: A revision opportunity may occur to each UE with probability equal to $p_{revision} = \lambda \cdot dt$, where dt is the time interval between two loops. If the revision occurs, the UE chooses to imitate at random one of the UEs of its group. Then it recalculates λ according to the obtained payoff. The same process is applied until the difference of each strategy's payoff compared with the average payoff of the population is lower that a limit ε.

Note that the strategy adaptation process in the proposed EGT-based algorithm does not rely on the knowledge of the strategy selection of the other players. For the evolution a UE requires a random matching with an opponent, a function that can be offered by a central controller (e.g. the SMF). Therefore, the amount of information exchange is reduced. The central controller will randomly match the UEs and stop the evolution process, if all payoffs are equal or differ by a small quantity.

The time interval (dt) between two repetitions must be higher than the communication time between the UE, the AMF, the SMF and the UPF that is going to carry the PDU session. dt is highly affected by the number of UPFs that are under the control of the SMF, since a large number of UPFs may result in increased processing delay for the SMF. Taking into consideration the timing requirements of the network service ($t_{service}$), and the number of iterations of the algorithm (L), the number of UPFs (N) under the SMF's control can be evaluated so that the following relationship is true:

$$N < F^{-1}\left(\frac{t_{service}}{L}\right) \quad (6)$$

Where F^{-1} is the inverse function that relates dt with N.

III. Numerical Results and Discussion

This section presents simulation results to validate our theoretical findings and evaluate the proposed algorithm performance. In the following we assumed a population of UEs that are organized into two groups. The UEs in each group can decide whether they want to use a local UPF at the edge of the network, that connects to a MEC, or to a UPF four times further away ($t_{prop_{cc}}/t_{prop_{mec}} = 4$), that connects to a central cloud as shown in Fig. 1. The UPF in the central cloud can process a greater number of requests, compared to the local UPFs, and is shared by all groups in the UE population whereas the local UPF is dedicated to the population inside a group. The traffic generated by each UE is assumed to be $\rho_{UE} = 100\ Mbps$. The limit ε of the algorithm is set to a payoff difference of 0.01. Fig. 2 illustrates our simulation results (full lines) and the theoretical results derived through the model of the replicator dynamics (doted lines) demonstrating good agreement between theory and simulation. More specifically, Fig. 2(a) plots the evolution of strategy shares among the population of UEs. It can be observed that the system converges after some iterations to the equilibrium. In equilibrium all UEs achieve the same delay (Fig. 2(b)) indicating the fairness of the scheme. The number of total iterations of the algorithm is of vital importance for network planning. As it was discussed in IIB, the number of iterations in combination with the time requirements of the service, can give an estimate (Eq. (6)) of the number of UPFs that the SMF can control, without compromising the stability of the system. Fig. 2 shows that less than 100 iterations are needed for the system to converge.

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