Learning based E2E Energy Efficient in Joint Radio and NFV Resource Allocation for 5G and Beyond Networks

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Abstract—In this paper, we propose a joint radio and core resource allocation framework for NFV-enabled networks. In the proposed system model, the goal is to maximize energy efficiency (EE), by guaranteeing end-to-end (E2E) quality of service (QoS) for different service types. To this end, we formulate an optimization problem in which power and spectrum resources are allocated in the radio part. In the core part, the chaining, placement, and scheduling of functions are performed to ensure the QoS of all users. This joint optimization problem is modeled as a Markov decision process (MDP), considering time-varying characteristics of the available resources and wireless channels. A soft actor-critic deep reinforcement learning (SAC-DRL) algorithm based on the maximum entropy framework is subsequently utilized to solve the above MDP. Numerical results reveal that the proposed joint approach based on SAC-DRL algorithm could significantly reduce energy consumption compared to the case in which R-RA and NFV-RA problems are optimized separately.

Index Terms—Resource allocation, Network Function Virtualization (NFV), E2E QoS, Energy Efficiency (EE), Soft Actor Critic (SAC).

I. INTRODUCTION

To support the exponential growth of traffic and various services, communication service providers (CSPs) need to redesign their infrastructure or move toward a flexible programmable infrastructure [1]. On the other hand, CSPs seek to increase capacity demands and upgrade their network in the shortest possible time. Network function virtualization (NFV) and softwarization are the key technologies that can meet the requirements of increasing the exponential traffic, various quality of services (QoS) requirements intended in the next generations of cellular networks, i.e., fifth-generation (5G) wireless cellular network [2]. NFV is emerged as a critical technology to reduce the network CAPEX and OPEX, and to time to market by virtualizing all the appliances such as servers, routers, storage, and switches [3]–[7]. NFV technology allows network functions to be run virtually on network servers as virtual network functions (VNFs), e.g., firewall, deep packet inspection, transcoding, and load balancing [2]. In this paper, we assume that VNF and network function (NF) are the same [8]–[10].

A. Background to NFV and Radio Resource Allocation

One of the critical challenges in the NFV-based network is resource allocation (RA) [5], [7], [10]. NFV resource allocation (NFV-RA) consists of three phases: 1) The first phase is the VNF service function chaining (VNF-SFC), in which the chain and the connection of VNFs are determined [11]. 2) The second phase is VNF Placement, in which the VNFs are mapped to the servers/virtual machines (VMs), and 3) The third phase is VNF scheduling in which the running time for each VNF is determined [10]. Each of the mentioned phases has a significant impact on the network performance, e.g., total cost and also QoS of users. Therefore, optimizing all these phases together can have a significant impact on reducing total costs and improving QoS of users, e.g., end to end (E2E) delay. Besides, in the radio part, we are faced to limited power resources and spectrum scarcity; thus, it is necessary to efficiently allocate radio resources, i.e., radio resource allocation (R-RA), to provide a variety of services while ensuring the QoS of each user. Therefore, to provide an E2E service, the NFV-RA and R-RA should be considered jointly [12], [13].

Network services have various requirements such as delay and data rate. Since delay is one of the requirements that affect all parts of the network, to provide services that require a specific delay, it is necessary to consider all parts of the network together. Also, due to the fact that different parts of the network interact with each other, it is necessary to consider all parts of the network together to optimize the total energy consumption. Machine learning (ML) are new approaches to solve optimization problems in all domains, e.g., network domain, that have recently received a great deal of attention [14]–[16]. ML, due to its data-driven nature, automatically learns the network and communication environment and dynamically adapts protocols without human intervention [14]–[16].

B. Related Works

In this section, we review the related works. For this purpose, we classify the related works into two main categories: NFV-based works and learning methods for RA.

1) NFV-RA: As mentioned above, the NFV-RA problems are divided into three categories: 1) SFC problems, 2) VNFs Placement problems, and 3) VNFs scheduling problems. Each of these categories is discussed in the following.
a) VNF Chaining: In the NFV-based network, the flow should be passed through a sequence of middleboxes in a particular order called SFC to provide a service [17]. A resource allocation architecture which enables energy-aware SFC for a software-defined network (SDN) based is proposed in [18] by considering constraints on delay, link utilization, and server utilization. To solve this problem, a heuristic algorithm is proposed. In [19], a VNF chaining problem is addressed to minimize bandwidth utilization while computing results within reasonable runtime. To solve the problem, a heuristic algorithm is proposed. In [20], a VNF chaining problem is formulated to minimize total CAPEX and OPEX costs. In [21], a VNF chaining problem, while considering the trade-off between resource consumption and operational overhead, is studied. An integer linear programming (ILP) model is utilized to solve this problem. In [22], a VNF Selection and chaining problem in SDN/NFV-enabled networks by considering minimum E2E delay is investigated.

b) VNF Placement: In [23], the VNF placement problem is formulated in which the computational resources such as processing and storage capacity of CPUs and the capacity of virtual links are considered. This problem is solved by a heuristic algorithm. In [24], a VNF placement problem is proposed to minimize the total cost by considering the limited space for allocating functions in each server. A linear relaxation approximation is used to solve this problem. An algorithm for VNF placement and CPU assignment to VNFs is proposed in [25], in which the proposed problem is solved by decoupled solution strategy leveraging on sequential decision making. A problem of placement and chaining is studied in [26]. In this problem, nodes and links latency and capacities are considered. In [27], the VNF placement optimization problem is formulated for achieving lower bandwidth consumption and lower maximum link utilization. A genetic algorithm is proposed to solve this problem. In [28], a VNFs placement and chaining problem is formulated to minimize the total cost, including the cost of deploying VNF instances, the cost of using surrogate servers, and the cost of communication. Moreover, in that work, the communication delays and processing delays of VNFs are considered. To solve the proposed algorithm, a heuristic algorithm is presented. A VNF placement cost minimization problem, taking the network stability into account, is formulated in [29]. The proposed problem is decomposed into an SFC and VNF mapping problem, which are solved by a genetic algorithm-based heuristic. In [30], VNF placement in the cloud data center to minimize the number of activated physical machines and consider time-varying workloads of physical machines is studied. The proposed problem is formulated as an integer linear programming (ILP) model, which is solved by a greedy-based algorithm. A Fully decentralized approach for online placement and optimization of VMs for NFV-based network is proposed in [31]. A VNF placement to optimize operational and traffic cost is formulated in [32]. To solve that problem, a sampling-based Markov approximation (MA) approach is applied which is a combination of Markov and matching algorithm. The joint VNF placement and admission control to maximize the network provider revenue in terms of bandwidth and capacity are investigated in [33]. The relaxation, reformulation, and successive convex approximation (SCA) methods are employed to solve this problem. In [34], a cross-layer resource optimization model and solution for wireless-enabled SFC is proposed to optimize VNF placement and route path by considering E2E downlink latency, including both wireless and wired delay.

c) VNF Scheduling: In [3], a VNF scheduling and placement algorithm is proposed in which the available buffer capacity and processing time of the VNFs are considered. A greedy-based method is used to solve the proposed algorithm. In [7], a scheduling problem for SDN-based system is proposed, which is solved with a two-stage approach. In [35], a joint VNF scheduling and traffic steering problem is formulated in which VNF transmission and processing delays are considered. To solve this problem, a genetic algorithm-based method is utilized. A matching-based algorithm for solving the VNF scheduling problem is presented in [36]. A deadline-aware VNF scheduling problem for ultra-low latency services is presented in [37] to maximize the number of admitted services. The proposed problem is solved by utilizing a tabu search-based heuristic method. In [38], an RA algorithm for VNFs placement and scheduling is studied.

2) Learning Methods for RA: In [39], a machine learning-enabled architecture is investigated to provide the demands of advanced vehicular Internet infrastructures. In [15], a VNF placement problem in SDN/NFV-enabled networks is formulated. To solve the proposed problem, a deep reinforcement learning (RL) Algorithm is proposed. A multi-objective resource allocation problem for NFV orchestration (NFVO), as a Markov decision process, is formulated in [40] in which A Q-learning based algorithm is proposed to solve this multiple objectives problem. In [41], a problem of scheduling VNFs is studied to minimize the overall completion time of all services by considering E2E delay requirements. To solve the problem with high efficiency and high accuracy, the authors utilized the RL algorithm to find the optimal scheduling policy. In [42], a novel method based on RL for performing dynamic SFC resource allocation in NFV-SDN enabled network is proposed. To design intelligent and efficient VNF selection and chaining for service function chaining requests, a deep learning-based two-phase algorithm is introduced in [22].

In all of the above works, the authors consider only one server hosts several VMs or several servers each of which hosts only one VM. The critical point is that several servers that host several VMs are not considered simultaneously in any of the above works. However, in real systems, each server can process multiple VMs simultaneously. As a result, considering multiple VMS on each server increases the complexity of the system model and requires new solutions. Most importantly, to provide some of the 5G and beyond (5G+) services, such as ultra-low latency services, the network should be considered from an E2E perspective which is not considered in all previous works. Furthermore, due to the resource limitation and 5G+ services requirements such as E2E delay, it is necessary to consider and optimize the NFV and radio parts jointly. Moreover, the main drawback of the above works is that the new solution methods, such as ML methods, are not applied.
to solve the optimization problem in the NFV-RA area.

C. Our Contributions

The main contributions of this paper can be summarized as follows:

- In this paper, a joint NFV-RA and R-RA optimization problem from the E2E perspective is proposed, in which QoS of the requested services are satisfied. In our proposed problem, our aim is to minimize the energy per service by considering the limitation of radio resources, i.e., power and spectrum, as well as the computational and storage capacities of core servers. Moreover, we consider multiple VMs per server in this work, which is a more realistic model and leads to increase in the complexity of formulation and, thus, the problem solution.
- We introduce a new approach for VNF chaining, placement, and scheduling by considering the network service delay in the closed-form expression with mathematical representation.
- Since the VNF chaining, placement, scheduling, and E2E-QoS for different services and radio resources satisfy Markov property, we model the optimization problem as a Markov decision process (MDP). The proposed MDP problem is subsequently solved by utilizing a state-of-the-art off-policy deep reinforcement learning (DRL) algorithm, namely soft actor-critic [43], which is based on the maximum entropy framework.
- A Python-based simulator is developed in the simulation to implement the proposed algorithm and other baseline algorithms.
- We provide numerical results for the performance evaluation of joint R-RA and NFV-RA algorithms for different network configurations. Our simulation results reveal joint R-RA and NFV-RA outperforms conventional ones by approximately 100% by increasing computational complexity.

D. Paper Organization

The rest of the paper is outlined as follows. In Section II, the system model and problem formulation are explained. The proposed solution is presented in Section III. In Section IV, the computational complexity and convergence of our solution are discussed. The simulation results are presented in Section V. Finally, in Section VII, the conclusion remarks is inferred.

Symbol Notations: Vector and matrices are indicated by bold lower-case and upper-case characters, respectively. A denotes set \( \{1, \ldots, A\} \), \( a(i) \) is the \( i \)-th element of set \( A \), and \( \mathbb{R}^n \) is the set of \( n \) dimension real numbers. Moreover, \( U_d[a, b] \) denotes the uniform distribution in interval \( a \) and \( b \) and \( |.| \) indicates absolute value.

II. SYSTEM MODEL AND PROBLEM FORMULATION

As shown in Fig. 1, we consider an E2E network consisting of a multi-cell radio access part and an NFV-based core part with several servers/nodes in this system model. Therefore, we describe the system model from both aspects, i.e., radio part and core part, in the following.

Remark 1. It is worth noting that the wireless channel state information (CSI), i.e., radio access network (RAN) parameters, changes faster than the parameters of the NFV, i.e., SFC. In this paper, we assume that the parameters of the radio and NFV parts are fixed in each optimization problem similar to the existing works [34, 44].

A. Radio Access Network Description

We consider a multi-cell network with a set of \( J = \{1, \ldots, J\} \) BSs which are connected to the core part. Moreover, we consider a set of \( U = \{1, \ldots, U\} \) users and a set \( K = \{1, \ldots, K\} \) subcarriers with bandwidth \( B \). We define the subcarrier assignment variable \( \rho_{u,j}^k \) with \( \rho_{u,j}^k = 1 \) if subcarrier \( k \) is allocated to user \( u \) at BS \( j \) and otherwise \( \rho_{u,j}^k = 0 \). We assume orthogonal frequency division multiple access (OFDMA) as the transmission technology in which each subcarrier is assigned at most to one user in each BS. Thus, the following constraint is introduced:

\[ C1: \sum_{u \in U} \rho_{u,j}^k \leq 1, \forall k \in K, j \in J. \]

Let \( h_{u,j}^k \) be the channel coefficient between user \( u \) and BS \( j \) on subcarrier \( k \). \( p_{u,j}^k \) be the transmit power from BS \( j \) to user \( u \) on subcarrier \( k \). \( a_{u,j}^k \), be the power of additive white Gaussian noise (AWGN) for user \( u \) at BS \( j \) on subcarrier \( k \), and \( I_{u,j}^k \) the is the inter-cell interference on user \( u \) at BS \( j \) over subcarrier \( k \). Thus, the received signal to interference and noise ratio (SINR) of user \( u \) at BS \( j \) on subcarrier \( k \) is \( \gamma_{u,j}^k = \frac{p_{u,j}^k h_{u,j}^k}{a_{u,j}^k + I_{u,j}^k} \), and the achievable data rate (in bits per second/Hz) of user \( u \) at BS \( j \) on subcarrier \( k \) is given by

\[ r_{u,j}^k = \rho_{u,j}^k \log(1 + \gamma_{u,j}^k), \forall u \in U, k \in K, j \in J. \]

Hence, the total achievable rate of user \( u \) at BS \( j \) is given by

\[ R_{u,j} = \sum_{k \in K} r_{u,j}^k, \forall u \in U, j \in J. \]

The transmit power limitation of BS \( j \) is

\[ C2: \sum_{k \in K} \sum_{u \in U} \rho_{u,j}^k p_{u,j}^k \leq P_{j}^{\text{max}}, \forall j \in J, \]

where \( P_{j}^{\text{max}} \) is the maximum transmit power of BS \( j \).

B. NFV Environment Description

Here, we illustrate how the generated traffic of each user is handled in the network by performing different NFs in the requested user’s NF set on the different servers/physical nodes by leveraging NFV. In this regard, we consider NFV-RA that consists of a new approach for the placement and scheduling phases. In the placement phase, we map each NF on the server that is capable to run that NF. Moreover, in the scheduling phase, all NFs are scheduled on each server. Note that we do not consider mapping virtual links on the physical links and leave it as an interesting future work as [3, 47]. Besides, similar to [48–50], we assume that the core network is fullmesh and there is a direct path between any two nodes in the network.

1Defined by European Telecommunications Standards Institute (ETSI) as the composition of Network Function(s) and/or Network Service(s), defined by its functional and behavioral specification [45].

2Standardized by ETSI organization for 5G and beyond [46].
We consider $S$ NS types whose set is $S = \{1, 2, \ldots, S\}$ and $M$ NFs whose set is $F = \{f_m \mid m = 1, \ldots, M\}$. Hereinafter, we use the term service instead of NS. The considered parameters of the paper are stated in Table 1. Each service $s$ is defined by the tuple $(\text{source node}, \Omega_s, D_{s}^{\text{max}}, R_{s}^{\text{min}})$ where $\Omega_s$ is the set of NFs which constructs service $s$ defined by $\Omega_s = \{f_{m}^{s}\}, m \in \{1, \ldots, M\}$, $D_{s}^{\text{max}}$ is the delay constraint for each packet of service $s$, and $R_{s}^{\text{min}}$ is the minimum required data rate of service $s$. Here, we define a known binary variable $\chi_{u,s}^{v} \in \{0, 1\}$ that indicates user $u$ at BS $j$ requests service $s$. Based on the data rate requirement of each service, we have:

$$C3: R_{u,j} \geq \sum_{s \in S} \chi_{u,s}^{v} R_{s}^{\text{min}}, \forall u \in U.$$

We consider a set of physical node/servers denoted by $N = \{1, \ldots, N\}$ in the network each of which has a limited amount of computing and storage resources. The CPU and storage resources of server $n$ is defined by the tuple $(L_n, \Upsilon_n)$ where $L_n$ is processing capacity (CPU cycle per unit time) and $\Upsilon_n$ is storage capacity of server $n$ (number of packets per unit time). Moreover, we consider a set of VMs indicated by $V = \{1, \ldots, V\}$ running on top of physical nodes and can host one or more NFs. Besides, VM $v$ needs a processing resource ($L_v^u$) and storage resource ($\Upsilon_v^u$) to run on server $n$. Furthermore, we define a known binary variable $e_{v}^{f_{m}}$ with $e_{v}^{f_{m}} = 1$ if VM $v$ can host NF $f_{m}$ and otherwise $e_{v}^{f_{m}} = 0$. We assume that each VM can process at most one function at each time $[3]$, but it can process any NF $[3]$, if capable to run it based on variable $e_{v}^{f_{m}}$.

To embed and schedule NFs, we first need to determine which server hosts which VM. Then, it must be determined how the NFs are to be scheduled in the VMs and servers. We introduce a binary variable $\beta_{u,j,v}^{f_{m},v}$ (i.e., VNF-placement variable) which denotes that NF $f_{m}$ of service $s$ for user $u$ at BS $j$ is executed at node $n$ in VM $v$, and is defined as

$$\beta_{u,j,v}^{f_{m},v} = \begin{cases} 1, & \text{NF } f_{m} \text{ of service } s \text{ for user } u \text{ at BS } j \text{ is executed at server } n \text{ in VM } v. \\ 0, & \text{Otherwise.} \end{cases}$$

Each NF of each service is performed completely at only one VM and server at a time $[35]$. Therefore, we have

$$C4: \sum_{n \in N} \sum_{v \in V} \beta_{u,j,v}^{f_{m},v} e_{v}^{f_{m}} \leq 1, \forall u \in U, j \in J, f_{m}^{s} \in \Omega_{s}, s \in S.$$

Moreover, we assume that NF $f_{m}^{s}$ needs a specific number of CPU cycles per bit to run on VM $v$ over the assigned server $n$, i.e., $\psi_{u,j,v}^{m}$. From the physical resource perspective, we assume that each server $n$ can provide at most $L_n$ CPU cycles per unit time. Therefore, by considering total required CPU cycles, we have the following constraint:

$$C5: \sum_{j \in J} \sum_{u \in U} \sum_{s \in S} \sum_{v \in V} \sum_{f_{m}^{s} \in \Omega_{s}} \beta_{u,j,v}^{f_{m},v} e_{v}^{f_{m}} (y_{u,j} f_{m}^{s} + \tilde{L}_{v}^{u}) \leq L_{n}, \quad \forall n \in N,$$

where $y_{u,j}$ is the packet size of the user $u$ at BS $j$. Here, we assume that the packet size is equal to the number of bits generated in a unit time $[3], [7], [35]$. Hence, the elapsed time of each NF $f_{m}^{s}$ for each bit on VM $v$ over server $n \in N$ is equal to $\frac{y_{u,j} f_{m}^{s}}{\psi_{u,j,v}^{m}}$, $\forall n \in N, f_{m}^{s} \in \Omega_{s}$. Therefore, the total processing delay of running NF $f_{m}^{s}$ on VM $v$ at server $n$ for each packet with packet size $y_{u,j}$ of user $u$ at BS $j$ is obtained as

$$\tau_{u,j,v}^{f_{m},v} = \frac{y_{u,j} f_{m}^{s}}{\psi_{u,j,v}^{m}}, \forall n \in N, f_{m}^{s} \in \Omega_{s}. \quad (4)$$

Additionally, we assume that each NF needs specific storage size, i.e., $\psi_{u,j,v}^{m}$, when it is running on VM $v$ on the server $n$. Moreover, each packet consumes $y_{u,j}$ buffer capacity, when it is waiting for running a NF on an assigned server. Hence, from the storage and buffer resource perspective, we consider that each server has a limited buffer and storage size, i.e., $\Upsilon_{n}$, which leads to the following constraint:

$$C6: \sum_{u \in U} \sum_{s \in S} \sum_{f_{m}^{s} \in \Omega_{s}} \sum_{j \in J} \sum_{v \in V} \beta_{u,j,v}^{f_{m},v} e_{v}^{f_{m}} \left(\psi_{u,j,v}^{m} + y_{u,j} \right) + \tilde{\Upsilon}_{v}^{u} \leq \Upsilon_{n},$$

where $\beta_{u,j,v}^{f_{m},v}$.
| Notation | Definition |
|----------|------------|
| J / J_{j} | Set/number/index of BSs |
| U / U_{j} | Set/number/index of users |
| K / K_{j} | Set/number/index of subcarriers with bandwidth $B$ |
| N / N_{i} | Set/number/index of servers/physical nodes |
| V / V_{i} | Set/number/index of VMs |
| F / F_{j} | Set/number/index of NFs |
| S / S_{i} | Set/number/index of services |
| $\Omega_{s}$ | Set of NFs which constructs service $s$ |
| $D_{m}^{\max}$ | Delay constraint for each packet of service $s$ |
| $R_{m}^{\min}$ | Minimum required data rate of service $s$ |
| $p_{m}^{\max}$ | Maximum transmit power of the BS $j$ |
| $\rho_{u,j}^{m}$ | Assignment of subcarrier $k$ to user $u$ at BS $j$ |
| $\psi_{u,j}^{m}$ | Transmit power of user $u$ from BS $j$ on subcarrier $k$ |
| $h_{u,j}^{m}$ | Channel coefficient between user $u$ and the BS $j$ on subcarrier $k$ |
| $\gamma_{u,j}^{m}$ | SINR of user $u$ at BS $j$ on subcarrier $k$ |
| $\tau_{u,j}^{f}$ | Achieved rate of user $u$ at BS $j$ on subcarrier $k$ |
| $\nu_{u,j}$ | Packet size of the requested service of user $u$ at BS $j$ |
| $q_{u,j}^{m,n}$ | Processing and storage demand of NF $f_{m}^{n}$ in service $s$ on VM $v$ on server $n$, respectively |
| $e_{u,j}^{m,n}$ | Processing delay of NF $f_{m}^{n}$ on VM $v$ on server $n$ for service $s$ |
| $\lambda_{u,j}$ | Processing and storage capacity of server $n$ respectively |
| $\bar{e}_{u,j}^{m,n}$ | Required Processing and storage capacity for running VM $v$ on server $n$, respectively |
| $\nu_{u,j,v}^{m,n}$ | VM $v$ hosts NF $f_{m}^{n}$ |
| $\gamma_{u,j,v}^{m,n}$ | Server mapping between NF $f_{m}^{n}$ of service $s$ for user $u$, and VM $v$ on host $n$ |
| $\phi_{u,j}^{m,n,v}$ | Required processing capacity to run NF $f_{m}^{n}$ on VM $v$ over the assigned server $n$ |
| $\psi_{u,j}^{m,n,v}$ | Required storage capacity to run NF $f_{m}^{n}$ on VM $v$ over the assigned server $n$ |
| $t_{u,j,n}^{f}$ | Start time of running NF $f_{m}^{n}$ of the requested service $s$ for user $u$ at BS $j$ on server $n$ in VM $v$ |
| $\delta_{u,j,n}^{m,n,v}$ | Ordering indicator between NF $f_{m}^{n}$ of service $s$ for user $u$ and NF $f_{s'}^{m,n}$ of service $s'$ for user $u'$ |

**TABLE I**

**NETWORK PARAMETERS AND NOTATIONS**

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### C. Latency Model

In NFV-RA, our main aim is to guarantee the service requirement, which includes maximum tolerable delay for each packet with size $y_{u,j}$ of the requested services while minimizing the energy consumption of physical nodes [3], [7], [35]. The total delay that we consider in our system model results from executing NFs, waiting time, and transmission time between nodes. In the following, we calculate the total delay resulting from scheduling.

Each NF should wait until its preceding function is processed before its processing can commence. The processing of each packet of service $s$ ends when its last function is processed. Therefore, the total processing time is the summation of the processing times of the NFs at the various VMs on servers. For scheduling of each NF on a server, we need to determine the start time of it. Therefore, we define $t_{u,j,n}^{m,n,v}$ which is the start time of running NF $f_{m}^{n}$ of the requested service $s$ for user $u$ at BS $j$ on server $n$ in VM $v$. Furthermore, we introduce a new variable $x_{u,j,n}^{m,n,v}$, in which, if NF $f_{m}^{n}$ of user $u$ at BS $j$ is running on VM $v$ at server $n$ after NF $f_{m'}^{n'}$ of user $u'$ at BS $j'$ is running on VM $v'$ at server $n'$, its value is 1, otherwise is 0. By these definitions, the starting time of each NF can be obtained in (3). The first part of this equation determines the priority of performing the NFs of the requested service by a specific user. The second part determines the priority of running each NF of user $u$ in relation to each NF of user $u'$. Thus, the execution time and location of each NF are determined. In the following, we clarify this equation with an example.

To demonstrate how we formulate the scheduling of NFs, the proposed scheduling policy is illustrated in Fig. 2. This figure is the state of the network assuming two services with several NFs, four servers, and three VMs. The processing time of each NF, $t_{u,j,n}^{m,n,v}$ is obtained by (2), i.e., $\tau_{u,j}^{f} = \frac{y_{u,j}^{s}}{q_{u,j}^{m,n}v}$. Each NF has a start time (denoted by $t_{u,j,n}^{m,n,v}$) to run on an assigned VM and elapses processing time (denoted by $\tau_{u,j,n}^{f}$) and is completed by the time given by $t_{u,j,n}^{m,n,v} + \tau_{u,j,n}^{f}$ on VM $v$ at server $n$. To make (3) clearer, suppose user 1 at BS 1 requests service 1, and user 2 at BS 2 requests service 2. As can be seen, for user 1 $f_{1}^{1}$ is executed after $f_{1}^{2}$ at VM 3 on server 4. Thus, we have $f_{1}^{1}, f_{2}^{2}, f_{3}^{3}$ and $f_{1}^{1}, f_{2}^{2}, f_{3}^{3}$. Moreover, as shown in this figure, $f_{1}^{1}$ of user 1 at BS 1 is executed at VM 1 on server 2 after $f_{1}^{2}$ of user 2 at BS 2 is executed at VM 2 on server 4. Thus, we have $f_{1}^{1}, f_{2}^{1}, f_{3}^{3}, f_{2}^{2}$ and $f_{1}^{1}, f_{2}^{1}, f_{3}^{3}, f_{2}^{2} = 0$. As can be seen, servers 3 and 1 are off, since based on our aim and solution algorithm, two servers from four servers are sufficient to ensure the requested requirements.

It is worth noting that our problem is performed for a snapshot assuming all the packets of the services which are generated in unit time are fetched into the network at the beginning of each unit time. Hence, the arrival time of all packets is the same and can be set to zero. Therefore, the total service chain delay for each user $u$ at BS $j$ on the requested service is inferred in (3), in which $\bar{B}_{n,n'}$ is bandwidth of link between node $n'$ to node $n$. Based on the delay requirement of each service, we have the following constraint:

$C8$: $D_{u}^{Total} \leq D_{s}^{\max}$, $\forall u \in U$.

### D. Objective Function and Optimization Problem

Our aim is to minimize the total energy per service in the network. To this end, we divide the total energy into three categories: 1) Radio part energy consumption, 2) CPU energy consumption, and 3) memory energy consumption. Therefore, the energy of the radio part is calculated as follows: where $\hat{t}$ is time unit, in which the optimization problem is solved. Moreover, the energy consumption of the CPU of servers consists of two parts: the energy consumption of the connected mode (when the server is working and host one or several
C7: $f_{u,j,n}^{m,v} f_{n}^{m,v} e_{v}^{m} \geq \max \left\{ \max_{\forall f_{m}^{v} \in \Omega_{s}, \forall e_{v}^{m} \in S} \left\{ \beta_{u,j,n}^{m,v} e_{v}^{m} \left( f_{u,j,n}^{m,v} + f_{u,j,n}^{m,v} \right) + \sum_{n' \in N} \sum_{v' \in V} \sum_{u' \in U} \sum_{v' \in V} y_{u,j}^{m,v} \right\}, \forall u \in U. \right\}$

Therefore, the total energy consumption function is given as

\[ E_{\text{CPU}}(\mathbf{B}, \mathbf{\tau}) = \sum_{n \in N, v \in V, u \in U} P_{\text{CPU}}^{v} \beta_{u,j,n}^{m,v} e_{v}^{m} \left( f_{u,j,n}^{m,v} + f_{u,j,n}^{m,v} \right) + \sum_{n' \in N} \sum_{v' \in V} \sum_{u' \in U} \sum_{v' \in V} y_{u,j}^{m,v} \] \tag{7}

Therefore, the total energy consumption function is given as follows \cite{51}:

\[ \Psi(\mathbf{P}, \rho, \mathbf{B}, \mathbf{\tau}) = \mu_{1} E_{\text{Radio}}(\mathbf{P}) + \mu_{2} E_{\text{CPU}}(\mathbf{B}, \mathbf{\tau}) \] \tag{8}

where $\mu_{1}$ and $\mu_{2}$ are constants and are used for scaling and balancing the energy of different resource types.

The gain of this approach is not only saving the consumption of the power in the active mode (i.e., under load) but also saving the power of the servers in the idle mode.

### E. Problem Formulation

Based on these definitions, our aim is to solve the following JRN-RA optimization problem:

\[ \max_{\mathbf{P}, \rho, \mathbf{B}, \mathbf{\tau}} \frac{\sum_{u \in U} \sum_{j \in J} \sum_{k \in K} t_{u,j}^{k}}{\Psi(\mathbf{P}, \rho, \mathbf{B}, \mathbf{\tau})}, \] \tag{9a}

s.t.: C1-C8 \tag{9b}

\[ \rho_{u,j}^{k} \in \{0,1\}, \quad \forall u \in U, j \in J, \quad k \in K, \] \tag{9c}

\[ \beta_{u,j,n}^{m,v} \in \{0,1\}, \quad \forall u \in U, \forall f_{m}^{v} \in \Omega_{s}, \forall s \in S, \] \tag{9d}

\[ f_{u,j,n}^{m,v} \in \{0,1\}, \quad \forall u, u' \in U, u \neq u', \] \tag{9e}

\[ \forall f_{m}^{v}, f_{n}^{v} \in \Omega_{s}, \forall v, v' \in V, \forall n, n' \in N, \] \tag{9f}

where $\rho = [\rho_{u,j}^{k}], \beta = [\beta_{u,j,n}^{m,v}], \mathbf{P} = [P_{u,j}^{k}]$. In problem (9c), constraints C1-C8 are defined in the previous section. Constraints (9c)-(9e) are for binary variables.

### III. MARKOV DECISION PROCESS BASED PROBLEM FORMULATION

Due to the arrival of unpredictable users’ requests, the state of the network, traffic, and capacity of the servers will be changed and will not be static. Thus, we are looking for a dynamic and appropriate solution to solve our proposed system. In this paper, we want to perform different NFs on the different VMs and assign VMs to the server/physical nodes. Since these choices are not specific and may have high dimensional state spaces, we adopt deep RL approaches for the joint radio and core resource allocation in the NFV-based network from the EE perspective. Hence, we investigate deep learning methods. Since we have compounded actions, such
as continuous and discrete variables, we propose a soft actor–critic (SAC) algorithm modeled as an MDP. The elements of the MDP, i.e., state, action, and reward, are defined as follows:

For each time step $t_p$, the state is forwarded for the actor and critic. The actual policy takes the state $s_{tp}$ and outputs an action $a_{tp}$, which results in a new state $s_{tp}$ and a reward $r_{tp}$.

### A. System States:

The system state is an abstraction of the environment, and the learner makes action decisions based on the states. The most influential parameter on the state of the network environment is channel gain. Therefore, the system state $s$ is defined as is the state space, and the state $s_{tp}$ ∈ $\mathcal{S}$ at $t_p$-th time slot that is equivalent to channel gain of all users at $t_p$-th time slot is represented as:

$$ s_{tp} = \{h_{u,j}^{k}(t_p)\}. \quad (10) $$

### B. Action space:

The learner takes an action by considering the network’s state because the network operates in a new state and transients from the current state of the network. The set of action space $\mathcal{A}$, which $a_{tp} \in \mathcal{A}$ executed in the $t_p$-th time slot is expressed as:

$$ a_{tp} = \{P(t_p), \rho(t_p), \beta(t_p)\}, \quad (11) $$

where, $P(t_p)$, $\rho(t_p)$, and $\beta(t_p)$ are the corresponding actions of state that mentioned before in time slot $t_p$.

### C. Reward Function:

After an action is taken, the environment will return an immediate reward $r_{tp}$ to the agent. In this system, the agent tries to improve the optimization problem (9), with the aim of maximization of EE. The benefit of the action is defined as the reward $r_{tp}$. Thus, the reward is denoted as:

$$ r_{tp} = c \sum_{u \in \mathcal{U}} \sum_{j \in \mathcal{J}} \sum_{k \in \mathcal{K}} r_{u,j}^{k} \frac{1}{\Psi(P, \rho, B, \tau)}, \quad (12) $$

where $c$ is a coefficient factor. Based on the actions that users take according to the state of the system, the system’s state will be changed. For instance, if the learning solution increases the objective function, the reward will be positive; otherwise, the reward will be negative.

### IV. PROBLEM SOLUTION WITH SOFT ACTOR-CRITIC DRL ALGORITHM

To solve our proposed MDP problem, we employ SAC DRL. The SAC algorithm consists of the following four parts:

- **Actor**: Separate policy DNN,
- **Critic**: value function DNNs,
- An off-policy method which enables reuse of the past experience stored in the memory $\mathcal{M}$,
- Entropy maximization to ensure stability.

### A. Soft Value Functions

The main objective of the RL agent is to find the policy $\pi(a_{tp} | s_{tp})$ to maximize the expected reward. $\pi$ is the parameter to show the stochastic policy that gives the probability of taking a specific action when the agent is in a certain state. Despite existing RL algorithms, to ensure that the agent can explore continually, an entropy term $-\log \pi(a_{tp} | s_{tp})$ is added to the reward in $[52]$. The objective with the expected entropy of the policy $\pi(a_{tp} | s_{tp})$, which is the parameter to show the stochastic policy, gives the probability of taking a certain action when the agent is in a certain state is termed as the entropy objective and written as:

$$ V^\pi = \mathbb{E}\left\{ \sum_{i=1}^{T'} \nu^{i \rho}[r_{tp} - \lambda \log \pi(a_{tp} | s_{tp})] | \pi \right\} \quad (13) $$

where $\nu^{i \rho}$ shows the discount factor. Moreover, $\nu \in [0,1]$ and $\lambda$ are the parameters that responsible for controlling the stochasticity of the optimal policy. Furthermore, $Q^\pi$ is the estimate of expected reward if the action $a_{tp}$ in state $s_{tp}$ according to the policy $\pi$ was taken. Q-value function:

$$ Q^\pi(s_{tp}, a_{tp}) = \mathbb{E}\left\{ \sum_{i=1}^{T'} \nu^{i \rho}[r_{tp} - \lambda \log \pi(a_{tp} | s_{tp})] | a_{tp}, s_{tp}, \pi \right\} \quad (14) $$

The relevance of state-value function and Q-function is:

$$ V^\pi(s_{tp}) = \lambda \log \int_{\mathcal{A}} \exp\left(\frac{1}{\lambda} Q^\pi(s_{tp}, a_{tp})\right) da \quad (15) $$

and the optimal policy for (13), according to the state and action that was chosen is defined as below:

$$ \pi^*(0 | s_{tp}) = \exp\left(\frac{1}{\lambda} (Q^\pi(s_{tp}, a_{tp}) - V^\pi(s_{tp}))\right) \quad (16) $$

Compared to the conventional actor-critic DRL algorithm $[53]$, and that the (15) is a LogSumExp function which is a soft maximum, the Q-value function and state-value function are also named as soft Q-value function and soft state-value function, respectively.

### B. Critic Networks:

In this section, among many effective methods $[54]$, we apply DNN to approximate value function due to its convergence and stability $[55]$. According to the goal of policy evaluation, soft Q-value $Q^\pi_{w_i}(s_{tp}, a_{tp})$ is approximated by a DNN which is symbolized by weight $w_i$. In this regard, we use memory $\mathcal{M}$, in which the new generated experience at each time step is stored, to increase system stability and elude the divergence. In this process, $w_i$ is updated from the memory $\mathcal{M}$ to fracture the correlations between samples. Hence, the loss function can be expressed as follows:

$$ L(w_i) = \mathbb{E}[\frac{1}{2} (\tilde{Q}^\pi_{w_i}(s_{tp}, a_{tp}) - H_{w_i}(s_{tp}, a_{tp}))^2], \quad (17) $$

where term $H_{w_i}(s_{tp}, a_{tp})$ is:

$$ H_{w_i}(s_{tp}, a_{tp}) = r_{tp} + \nu V^\pi. \quad (18) $$
As previously explained, to update the weight of critic network, i.e., $w_i$, with gradient decent method to minimize the loss function $L(w_i)$, we have:

$$w_i(new) = w_i(old) - \alpha_w \nabla_{w_i} L(w_i(old)), \quad (19)$$

where $\alpha_w$ is the learning rate of the critic which is a positive value and $\nabla_{w_i} L(w_i)$ is the gradient of $L(w_i)$ and achieved by:

$$\nabla_{w_i} L(w_i) = \nabla_{w_i} \hat{Q}(w_i(s_t, a_t)) | \hat{Q}(w_i(s_t, a_t)) - H_{w_i}(s_t, a_t)].$$

### C. Actor Networks:

In this part based on a policy improvement approach, the objective function can be written as:

$$L(\delta_i) = \mathbb{E}[-\frac{1}{2}(\lambda \log \pi_{\delta_i}(s_t | s_t) + H_{\delta_i}(s_t, a_t))^2], \quad (21)$$

where term $H(s_t, a_t)$ is:

$$H_{\delta_i}(s_t, a_t) = Q_\pi(s_t, a_t) - V^\pi(s_t). \quad (22)$$

In a similar way of critic network, to update the weight of actor network $\delta_i$ with gradient decent method to minimize the loss function $L(\delta_i)$, we have:

$$\delta_i(new) = \delta_i(old) + \alpha_{\delta_i} \nabla_{\delta_i} L(\delta_i(old)) \quad (23)$$

where $\alpha_{\delta_i}$ is the learning rate of the actor network and $\nabla_{\delta_i} L(\delta_i)$ is the gradient of $L(\delta_i)$ and achieved by:

$$\nabla_{\delta_i} L(\delta_i) = \nabla_{\delta_i} V^\pi(s_t)[-H(s_t, a_t) + \lambda \log \pi_{\delta_i}(a_t)]. \quad (24)$$

### D. The Soft Actor-Critic DRL Algorithm

The duty of agent is divided as follows:

- The actor network: mapping states to actions,
- The critic network: estimating states and state-action couple,
- The memory $M$: storing experience.

The actor network with the suitable approach of finding the right policy $\pi_{\delta_i}(0 | s_t)$, which will be trained based on (16), according to the current state $s_t$, selects and executes an action $a_t$. In this step the neural network, depending on whether the action is well chosen or not, the agent receive rewards or punishments, respectively. Then, the next state $\tilde{s}_t$ is characterized and memory $M$ store this tuple $\langle s_t, a_t, r_t, \tilde{s}_t \rangle$. The critic network samples randomly from the tuples that are stored in the memory $M$, with the approach of elimination of temporal correlations between samples and train the state-value and Q-value. This learning process is intermittent sampling of the environment and updating the network until the final state or the network time-out. To understanding the better concept of this cycle, we propose Algorithm 1.

**Algorithm 1: Soft Actor-Critic Algorithm**

1. Initialize parameters $w_i, \delta_i$ and empty memory $M$
2. Set target parameters equal to main parameters
3. for each iteration
   for each environment step:
     Observe state $s_t$, and select action $a_t \sim \pi(0 | s_t)$
     Execute $a_t$ in the environment
     Observe next state $\tilde{s}_t$, reward $r_t$
   for each gradient step:
     $w_i(new) \leftarrow w_i(old) - \alpha_w \nabla_{w_i} L(w_i(old))$
     $\delta_i(new) \leftarrow \delta_i(old) + \alpha_{\delta_i} \nabla_{\delta_i} L(\delta_i(old))$
4. end for
5. output parameters: $w_i, \delta_i$

### V. COMPUTATIONAL COMPLEXITY AND CONVERGENCE ANALYSIS

#### A. Computational Complexity

The proposed system’s computational complexity is one of the key and practical criteria of the proposed system. Thus, we analyze the computational complexity of our proposed system model from two perspectives: training process and running process.

- **Training Process:** In most of the papers such as [15],[22], the authors ignored the computation complexity of the training process and assumed that the training process happens in off-line mode, and its computation complexity is proportional to the size of the training data and duration of the training. We consider the number of neurons on lth and kth layer of the actor and critic network as $I^l$ and $V^k$, respectively. Hence, the total computational complexity of the training process is $O(\sum_{k=2}^{L-1} (I^{l-1}I^l + I^lI^{l+1} + \sum_{k=2}^{K-1} (V^{k-1}V^k + V^kV^{k+1})) [56].$

- **Running Process:** In this part, we propose the computational complexity of the actor critic network. The internal computations of neural network algorithms depends on the architecture, the number of neurons, and the number of layers. Besides, in an algorithm consistent with deep RL, the number of states and actions is related to the number of neurons and neural network layers. Therefore, the computational complexity is in order of $O(B \times (2 \times HZ) \times (J \times U \times S \times V \times M))$ in which $B$ is the training batch, $H$ is the number of neurons in hidden layer $Z$, $J, U, S, V$, and $M$ are the numbers of BSs, users, NS, VMs, and NFVs, respectively.

#### B. Convergence Analysis

In this section, we evaluate the convergence of the SAC algorithm. According to Q-function in [14], the solution can converge to the optimal Q-function as $t \to \infty$ with probability 1, if the learning rates of the algorithm $\alpha_w$ and $\alpha_{\delta_i}$ are deterministic, non-increasing, and satisfy [57]:

$$\sum_{0}^{\infty} \alpha_w = \infty, \quad \sum_{0}^{\infty} (\alpha_w)^2 < \infty, \quad (25)$$
and $|t_p|$ be bounded [58]. With the aim of fast convergence and training our neural network effectively, we utilize the inverse time decaying learning rate that uses the large learning rate in the first episodes to prevent the network from getting stuck in a bad local optimum trap near the initial point and uses the small learning rate in the last training epochs in order to converge to a good local optimum [59]. The convergence of our proposed algorithm is also analyzed through simulations results in Section [VI].

Algorithm 2: Actor-critic methods consist of action-value $Q$ or state-value $V_{II}$

1. Initialize randomly $s, \theta, w$
2. For $t = 1, \ldots, T$:
   1. Sample reward $r_t$, $R_{tp}(s, a)$ and next state $s' \sim P(s' \mid s, a)$
   2. Then sample the next action $a' \sim \pi_\theta(a' \mid s')$
   3. Update the policy parameters: $\theta_{tp} \leftarrow \theta_{tp}(\pi_\theta(a') + a_w \nabla J_i(\theta_{tp}(s, a)))$
   4. Compute the correction (TD error) for action-value at time $t$: $\delta_t = \alpha[R_{tp}(s', a') + \gamma \max_{a'} Q_{tp}(s', a') - Q_{tp}(s, a)]$
   5. And use it to update the parameters of action-value function: $w_{tp}(new) \leftarrow w_{tp}(old) + a_w \nabla L(w_{tp}(old))$
3. Update $a \leftarrow a'$ and $s \leftarrow s'$.

Algorithm 3: Join Radio and Core Resource Allocation

1. Initialize total reward $r_t = 0$
2. For $t = 1, \ldots, T$ do
3. For $u = 1, \ldots, U$ do
4. The agent take an action $a$ with considering state $s$.
5. If constraint $C1-C8$ then
6. Calculate the obtained rate for user $u$
7. Calculate the EE by $[12]$

Algorithm 4: Actor-critic methods consist of action-value $Q$ or state-value $V_{II}$

1. Initialize randomly $s, \theta, w$
2. For $t = 1, \ldots, T$:
   1. Sample reward $r_t$, $R_{tp}(s, a)$ and next state $s', \tilde{s} \sim P(s' \mid s, a)$
   2. Then sample the next action $a' \sim \pi_\theta(a' \mid \tilde{s})$
   3. Update the policy parameters: $\theta_{tp} \leftarrow \theta_{tp}(\pi_\theta(a') + a_w \nabla J_i(\theta_{tp}(\tilde{s}, a)))$
   4. Compute the correction (TD error) for action-value at time $t$: $\delta_t = \alpha[R_{tp}(s', a') + \gamma \max_{a'} Q_{tp}(s', a') - Q_{tp}(s, a)]$
   5. And use it to update the parameters of action-value function: $w_{tp}(new) \leftarrow w_{tp}(old) + a_w \nabla L(w_{tp}(old))$
3. Update $a \leftarrow a'$ and $s \leftarrow \tilde{s}$.

VI. SIMULATION RESULTS

In this part, we consider a square area $1000m \times 1000m$ with 4 BSs, and the users are randomly distributed there. Moreover, we assume 10 subchannels with the frequency bandwidth of 200 kHz, the maximum power of each BS is set to 40 watts, and the minimum data rate of the downlink is set to 1 bps/Hz. In addition, our proposed system has 5 VNFs. Since each VNF require different processing parameters as $\pi_{\text{user}}$, we define some VNFs in Table III [60]. Moreover, we represent three types of SFCs by changing the order of six VNFs in Table III. Also, we show the processing requirements in terms of bandwidth $\delta$ and maximum tolerated delay $\varphi$ for all SFCs. The upper bound for the total service chain delay is set between 75 to 100 ms [15]. Furthermore, we assume that each node can host 6 VMs, and each VMs node can host 6 VNF at most. The capacities of bandwidth and memory of each physical link and node are set to 1 Gbps and 1 Gbyte, respectively. Moreover, the CPU capacity of each node is set to 1200 CPU cycle/bit [61]. In the training process, the value of loss function is Mean Square Error (MSE). From the commuting services point of view, we should explain that at the start of each experiment, we assume that each SFC request consists of six VNFs.

It is worth noting that the source code of the proposed method is written with Python language with TensorFlow library [62] with Adam optimizer. Also, more details for configuration of the neural network are summarized in Table IV. Besides, the sources codes of the proposed method and baselines are available in [?].


### TABLE III

| SFC               | Chained VNFs | Latency ($\mu s$) | Bandwidth (kb/s) |
|-------------------|--------------|-------------------|------------------|
| Web Service       | NAT-FW-TM-WOC-IDPS | 500               | 100              |
| VoIP              | NAT-FW-TM-FW-NAT | 100               | 64               |
| Video Streaming   | NAT-FW-TM-VOC-IDPS | 100               | 4                |

### TABLE IV

| Parameter                        | Value       |
|----------------------------------|-------------|
| Number of sub-carriers           | 10          |
| Total available bandwidth        | 200 KHz     |
| Number of BSs                    | 4           |
| Capacity of transaction memory   | 100000      |
| Batch size                       | 32          |
| Actor network learning rate      | 0.00001     |
| Critic network learning rate     | 0.0001      |
| Moving average hyper parameter   | 0.05        |
| AWGN power                       | -170 dbm    |
| Number of hidden layer of DNN    | 2, 3, 4, 5, 6 [17] |
| Number for neuron in each layer  | 1024, 500, 250 [62] |

### TABLE V

| Methods       | Complexity      |
|---------------|-----------------|
| SAC           | $O(B(2 \times HZ))$ |
| DDPG          | ..              |
| MADDPG        | ..              |

### A. Comparison between Joint Approach and Disjoint Approach

In this system model, we consider a joint radio and core resource allocation framework. In this part, we investigate the comparison between our proposed joint framework and disjoint framework in which the resource allocation optimization problem for RAN and core part are performed separately. To this end, we rewrite the problem formulation as two separate problems in the following. Hence, the R-RA problem formulation can be written as:

$$\max_{P,\rho,\beta} \sum_{u \in U} \sum_{j \in J} \sum_{k \in K} \mu_1 E(P, \rho)^{Radio}_{u,j,k},$$

s.t. C1-C2.

This new optimization problem can be solved by SAC algorithm. On the other hand, NFV-RA optimization problem can be summarized as follow:

$$\max_{P,\rho,\beta} \sum_{u \in U} \sum_{j \in J} \sum_{k \in K} \mu_2 E(B, \tau)^{CPU}_{u,j,k},$$

s.t. C3-C9.

We also solved the above problem by SAC algorithm. To solve above problems independently, first we solve R-RA problem. After that, we consider the obtained rate from radio part. Then we set the radio part delay as 10ms. For the sake of evaluating the performance of the proposed SAC method, we consider DDPG and multi-agent DDPG (MA DDPG) as baselines. Table shows the superiority of the SAC method, in terms of complexity, and the comparison with other method that considered as a baselines. As we depict in Fig, it is assumed that the core network and radio part have independent agents in which the agents report the obtained reward to a central neural network called global critic network. The global critic network calculates the total reward and critics between the agents. By updating the parameters of the radio and the core agents, these agent try to give better reward and minimize their loss function, gradually. It’s worth noting that the global critic just have the global reward that is obtained from radio and core agents.

As shown in Fig. EE in the disjoint approach is one-half of the joint approaches, i.e., SAC and DDPG. The reason for this is that in the disjoint approach, two problems are solved entirely independently of each other, and thus, we are faced with two problems that optimize the desired parts, e.g., RAN and core, regardless of the E2E view. As stated above, the global critic network calculates the total reward and critics between the agents. Therefore, it is expected that MA DDPG method has better performance than the disjoint approach which is revealed in Fig.

### B. Effects of Number of the Service Requests

As can be seen in Fig. by increasing the number of users to 10 users, the EE increases with increasing number of users. This is due to the fact that by increasing number of users, the network consumes more energy to ensure new users’ rate and delay requirements. Thus, the total data rate in the network is increased while the total energy is constant. Furthermore, as can be seen by increasing the number of users up to 20, the EE remains constant. It stems from the fact that by increasing the number of users, we reach a point that all the network energy is consumed to guarantee the requirements of all users. Thus, with the request of a new user, the network has no resources to guarantee the requirements of that user. As a result, the new user or one user who has a negative impact on EE is rejected. Therefore, the total data rate remains constant from one point in the figure onwards. The total network energy consumption is also constant and at its maximum value; hence, the EE remains constant.

### C. Effects of Minimum Data Rate

As we show in Fig the average EE is decreased by increasing the minimum data rate of the requested services. This is due to the fact that more energy is required to provide higher data rate. On the other hand, because of the resource limitations, i.e., energy limitation, the total accepted user is decreases by increasing the minimum data rate of the services. Therefore, the EE is decreased by increasing the minimum rate requirement.

### D. Effects of Maximum Tolerable Time of the Services

Based on constraint (C8) and Eq. it is obvious that more energy is required to guarantee smaller delays, and as a result, fewer users can be accepted due to the limitation...
Fig. 3. Comparing between the methods that are evaluated in this paper. In disjoint method, the core agent and radio agent selected their action based in the network state, independently. Similarly, in MA DDPG, each of the agents take the actions independently, but, they just report the obtained reward to the global critic. In addition the details of SAC and DDPG methods are written in Al 4 and 5, respectively.

Fig. 4. EE for number of the requested services

Fig. 5. Average EE versus the minimum data rate of the requested services.

of energy resources. As we depicted in Fig[6] by increasing the maximum tolerable time of the services, average EE of the network increases. Moreover, as stated before the disjoint approach performs worse than the other approaches, e.g., MA
DDPG, DDPG, and joint SAC.

E. Effects of the Coefficients

As can be seen in Fig. 7 by increasing the coefficient of core in the different methods, the agents try to maximize the EE in the core network. As a result, the agents select the VMs that have lower energy consumption. By selecting these VMs, there is the possibility that the physical path between the source node and destination cannot guarantee the maximum tolerable delay of the services. On the other hand, some users cannot be admitted due to the limited computation resources in these VMs. Moreover, the total energy consumed in the core network is significantly less than the radio part; thus, the average EE in the network is very similar to the average efficiency in the radio part of the network, as is shown in Fig.7(c) and Fig.7(b). Furthermore, due to the lower energy consumption in the core network, the average EE in the core network is remarkably higher than EE in the radio part, as can be seen in Fig.7(a).

F. Comparing Signaling Overhead in the proposed method and the Baselines

In each method, the agents need to have information such as the states and obtained rewards to take the actions. Thus, this information must be intercommunicated between the resource orchestrator and the radio part and core network [63]. To measure and model this information, we assume that each element of the channel gain matrix can be decoded as a fixed-length 16-bit binary string. Consequently, we use the type ‘float16’ in Numpy library in Python. Based on this, by considering a system with $B$ BSs and $J$ subchannels and $U$ users, the size of the channel gain matrix in a binary model is equal to $16 \times B \times J \times U$. Similarly, the local reward that each agent obtains can be modeled as a fixed-length 16-bit binary string. Finally, we summarize the total signal overhead in each episode for the proposed method and the baselines in Table VI.

VII. CONCLUSION

In this paper, we proposed a joint radio and NFV resource allocation to maximize EE (EE) by satisfying E2E QoS for different service types. In this regard, we formulated an optimization problem in which power and spectrum resources are allocated in the radio part. In the core part, the chaining,
placement, and scheduling of VNFS are performed to guarantee the QoS of all users. We modeled this joint optimization problem as a Markov decision process (MDP) by considering time-varying characteristics of the available resources and wireless channels. Thus, we applied a soft actor-critic deep reinforcement learning (SAC-DRL) algorithm based on the maximum entropy framework to solve the proposed MDP problem. Simulation results revealed that the proposed joint approach based on SAC-DRL algorithm could significantly reduce energy consumption compared to the case in which R-RA and NFV-RA problems are optimized separately.

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