Leveraging mixed-strategy gaming to realize incentive-driven VNF service chain provisioning in broker-based elastic optical inter-datacenter networks

Leveraging Mixed-Strategy Gaming to Realize Incentive-Driven VNF Service Chain Provisioning in Broker-based Elastic Optical Inter-Datacenter Networks [Invited]

Xiaoliang Chen, Zuqing Zhu, Jiannan Guo, Sheng Kang, Roberto Proietti, Alberto Castro, and S. J. B. Yoo

***Abstract*—This paper investigates the problem of how to optimize the provisioning of virtual network function service chains (VNF-SCs) in elastic optical inter-datacenter networks (EO-IDCNs) under EON and DC capacity constraints. We take advantage of the broker-based hierarchical control paradigm for the orchestration of cross-stratum resources and propose to realize incentive-driven VNF-SC provisioning with a noncooperative mixed-strategy gaming approach. The proposed gaming model enables tenants to compete for VNF-SC provisioning services due to revenue and quality-of-service incentives and therefore can motivate more reasonable selections of provisioning schemes. We detail the modeling of the game, discuss the existence of the Nash equilibrium states and design an auxiliary graph based heuristic algorithm for tenants to compute approximate equilibrium solutions in the games. A dynamic resource pricing strategy, which can set the prices of network resources in real time according to the actual network status, is also introduced for EO-IDCNs as a complementary method to the game-theoretic approach. Results from extensive simulations that consider both static network planning and dynamic service provisioning scenarios indicate that the proposed game-theoretic approach facilitates both higher tenant and network-wide profits and improves the network throughput as well compared with the baseline algorithms, while the dynamic pricing strategy can further reduce the request blocking probability with a factor of $\sim 2.4\times$.**

***Index Terms*—Virtual network function service chain (VNF-SC), Broker-based elastic optical inter-datacenter networks (EO-IDCNs), Mixed-strategy gaming, Dynamic resource pricing.**

I. INTRODUCTION

THE rapidly expanding datacenter (DC) networks and ubiquitous cloud-driven applications are driving the needs for intelligent service provisioning paradigms for inter-DC networks that can support high-capacity end-to-end services with flexible service requirements [1], [2]. Among all the recently devised technologies, network function virtualization (NFV), especially when coupled with software-defined networking (SDN), provides an unprecedented opportunity for network operators to customize their infrastructures adapting to the actual application profiles [3]. In particular, NFV can improve the flexibility and cost-efficiency of service provisioning by replacing proprietary hardware deployments with virtual network functions (VNFs, *e.g.*, firewalls, load balancer *etc.*) implemented based on generalized network and IT resources such as bandwidth, CPU cycles and memories. As one of the most important application scenarios of NFV, VNF service chaining (VNF-SC) steers user traffic through service function chains formed by sequences of VNFs instantiated in DCs to meet diverse service requirements [4]. Therefore, how to coordinate the configurations of VNFs and service paths to realize joint optimizations of network and IT resources becomes the key problem of VNF-SC [5]–[8].

Meanwhile, elastic optical networking (EON) [9], [10] has emerged as a promising technique for building DC interconnections, realizing elastic optical inter-DC networks (EO-IDCNs) [11], [12]. The problem of optimizing VNF-SC provisioning in EO-IDCNs becomes especially important due to the unique spectrum allocation schemes in EONs [13]. In [14] and [15], Xia *et al.* for the first time studied the problem of forming optical service function chains in wavelength-switched optical DC networks, and proposed a binary integer programming model as well as an alternative heuristic algorithm to optimize the usages of optical-to-electrical-to-optical (O/E/O) convertors. The provisioning algorithms for realizing multicast NFV trees in EO-IDCNs was investigated in [13], where the authors designed both mixed integer linear programming model and heuristic algorithms to jointly optimize the placement of VNFs and the routing and spectrum assignment of multicast trees. The same authors then formulated an optimization model for VNF-SC provisioning in EO-IDCNs to minimize the amount of deployed spectrum and VNF resources for the given traffic model [16]. More recently, Wang *et al.* further extended the concepts of service function chains and trees to consider the provisioning of VNF graphs with arbitrary topologies in multi-domain EO-IDCNs [17]. Nevertheless, the aforementioned studies all assumed centralized network control and management for EO-IDCNs, *i.e.*, optimizing the allocation of network and IT resources jointly by assuming the global visibility of DCs and EONs, which violates the autonomy of each administrative domain. Such a centralized network control and management architecture is unrealistic for the global Internet spanning many autonomous systems or domains [18]–[21]. Meanwhile, incentives from users, *e.g.*, heterogeneous quality-of-service requirements and service budgets, have not been addressed for VNF-SC provisioning in EO-IDCNs so far.

X. Chen, R. Proietti, A. Castro and S. J. B. Yoo are with the Department of Electrical and Computer Engineering, University of California, Davis, Davis, CA 95616, USA (Email: {xlichen, sbyoo}@ucdavis.edu).

Z. Zhu, J. Guo and S. Kang are with the School of Information Science and Technology, University of Science and Technology of China, Hefei, Anhui 230027, P. R. China (Email: zqzhu@ieee.org).

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In this paper, we extend our work in [22] to investigate how to realize efficient incentive-driven VNF-SC provisioning in broker-based EO-IDCNs, where a broker plane lies on top of the domain manager plane to orchestrate the configurations of network and IT resources. We model the problem as a noncooperative game, in which tenants compete with each other for VNF-SC provisioning services. Specifically, we assume that the profit of each tenant is related to the resource consumption cost and the achieved end-to-end service latency, and propose a mixed-strategy game-theoretic approach for tenants to find approximate equilibrium solutions in the games. In order to motivate tenants to use network resources more reasonably, we further design a dynamic resource pricing strategy for EO-IDCNs which can set the prices of network resources in real time according to the actual network status. Extensive simulations that consider both static networking planning and dynamic service provisioning scenarios are performed, and simulation results verify the effectiveness of the proposed game-theoretic approach and the dynamic pricing strategy.

The rest of the paper is organized as follows. Section II elaborates on the operation principle of broker-based EO-IDCNs and formally defines the problem of incentive-driven VNF-SC provisioning. Sections III and IV present the detailed designs for the mixed-strategy game-theoretic approach and the dynamic resource pricing strategy respectively. Section V shows the simulation results and Section VI summarizes this paper.

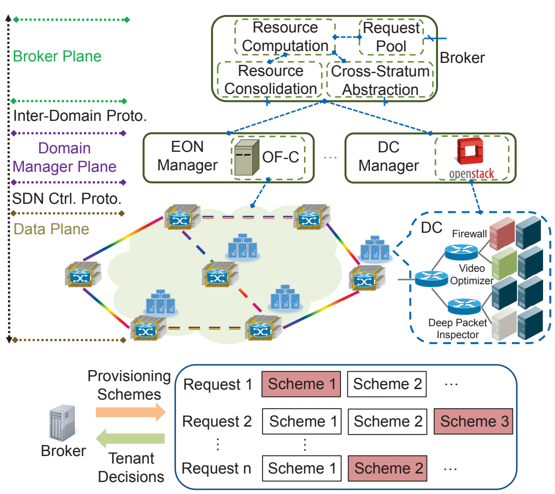

Fig. 1. Block diagram of a broker-based EO-IDCN.

II. Incentive-Driven VNF-SC Provisioning Framework

A. Operation Principle

Fig. 1 shows the block diagram of a broker-based EO-IDCN enabling incentive-driven VNF-SC provisioning. In the EO-IDCN, a number of geographically distributed DCs are interconnected by the EON, each of which provides the services for different types of VNFs. Above the data plane, EON and DC managers operate their substrate networks through SDN controllers (*e.g.*, OpenFlow controller, OpenStack *etc.*), while the broker interacts with domain managers to coordinate the

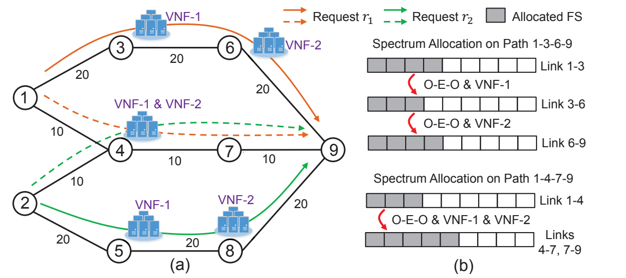

Fig. 2. An example for incentive-driven VNF-SC provisioning in EO-IDCNs, (a) topology and provisioning schemes and (b) spectrum allocation for VNF-SCs.

cross-stratum resource (*i.e.*, network and IT resources) allocations. Specifically, upon receiving tenant VNF-SC requests, the broker can collect abstractions regarding network connectivity and resource utilization from domain managers and calculate provisioning schemes accordingly. Note that, the broker may provide multiple provisioning schemes to each tenant while tenants select the most appropriate ones to use. Once the provisioning schemes have been confirmed by tenants, the broker informs related domain managers to configure the corresponding VNFs and elastic lightpaths.

Fig. 2 presents an illustrative example for the aforementioned VNF-SC provisioning paradigm. Here, the broker calculates two provisioning schemes labeled by the solid and dashed lines respectively for each request. The potential spectrum allocations for paths 1→3→6→9 and 1→4→7→9 are depicted in Fig. 2(b), with an O/E/O conversion being performed in each intermediate node where VNFs are configured. We can see that the frequency slot (FS) and O/E/O consumptions can vary significantly with the different placement of VNFs. This is because the placement of VNFs can divide an end-to-end path into several lightpaths where the modulation and spectrum assignment can be performed independently. For the sake of simplicity, we assume that the resource cost for using each provisioning scheme in this example equates to the sum of the weights of all the traversed links. It is interesting to notice that although the provisioning schemes labeled by dashed lines offer lower cost, tenants will not unalterably select them due to the fact that the sharing of the processing of VNFs in node 4 may introduce prolonged service latencies or even service blocks.

B. Problem Definition

We model the EO-IDCN topology as $G(V, E, V_D)$, with V and E representing the sets of links and nodes and V_D being a subset of V which contains the nodes where DCs locate. The set of VNFs instantiated in DC n ($n \in V_D$) is denoted as Θ_n. We denote a VNF-SC request as $r(s, d, b, T, \Gamma)$, where s and d are the source and destination nodes, b is the bandwidth requirement, T is the service duration and Γ conveys the demanded VNFs. Given the set of provisioning schemes $\mathcal{P}_i$ by the broker, the objective of each request r_i is to select a scheme $\mathcal{P}_{i,k} \in \mathcal{P}_i$ that maximizes its profit defined as,

$$U_{i,k}^{\psi^{-i}} = \frac{\beta_i - c_{i,k}}{\tau_i + D_{i,k}^{\psi^{-i}}}, \tag{1}$$

where β_i is the budget of r_i for the service, $c_{i,k}$ is the resource consumption cost, τ_i is a parameter representing r_i's sensitivity to latency, and $D_{i,k}^{\psi^{-i}}$ is the achieved end-to-end service latency (that is, the total time it takes per bit of data to traverse the service chain) given the other requests' strategies ψ^{-i} ($\psi^{-i} = \psi \setminus \psi_i$). Here, ψ denotes the strategy profile that contains the provisioning schemes used by all the requests, *e.g.*, $\psi_i = \mathcal{P}_{i,k}$ if r_i uses $\mathcal{P}_{i,k}$. Eq. 1 actually indicates that each request will try to jointly optimize the resource consumption and the achieved quality-of-service (*i.e.*, latency). We assume that $c_{i,k}$ is determined by the usages of FS's ($\chi_{FS}^{i,k}$), O/E/O converters ($\chi_{OEO}^{i,k}$) and IT resources ($\chi_{IT}^{i,k}$), *i.e.*,

$$c_{i,k} = \left(\chi_{FS}^{i,k} \cdot p_{FS} + \chi_{OEO}^{i,k} \cdot p_{OEO} + \chi_{IT}^{i,k} \cdot p_{IT}\right) \cdot T_i, \quad (2)$$

where p_{FS}, p_{OEO} and p_{IT} are the unit prices per provisioning period for FS, O/E/O and IT resource usages, respectively. Meanwhile, to obtain $D_{i,k}^{\psi^{-i}}$, we can calculate the signal propagation time $l_{i,k}$ and the processing time of VNFs on $\mathcal{P}_{i,k}$. While $l_{i,k}$ can easily be derived according to the path length, we can model the processing of tenant traffic in each VNF as an M/M/1 queue by assuming the tenant traffic as the input queue and the processing core of the VNF as the single server. Consequently, $D_{i,k}^{\psi^{-i}}$ is obtained as,

$$D_{i,k}^{\psi^{-i}} = l_{i,k} + \sum_{n \in V_D} \sum_{m \in \Theta_n} \frac{g_{i,k}^{n,m}}{\varsigma_{n,m} - \phi_i(b_i) - \sum\limits_{\mathcal{P}_{t,j} \in \psi^{-i}} g_{t,j}^{n,m} \phi_t(b_t)}, \quad (3)$$

$$s.t. \quad \varsigma_{n,m} - g_{i,k}^{n,m} \left(\phi_i(b_i) + \sum_{\mathcal{P}_{t,j} \in \psi^{-i}} g_{t,j}^{n,m} \phi_t(b_t)\right) > 0, \forall n, m, \quad (4)$$

where $\varsigma_{n,m}$ is the capacity limit of the m-th VNF in DC n, $g_{i,k}^{n,m}$ is a boolean parameter indicating whether $\mathcal{P}_{i,k}$ uses the related VNF, and function $\phi_i(\cdot)$ maps the data rate of r_i to its requirement on VNF processing capacity. Note that, we introduce the capacity limit $\varsigma_{n,m}$ corresponding to the processing rate of each VNF to avoid infinite processing time of VNFs[1]. In case Eq. 4 is not satisfied or collisions of spectrum utilization occur among the tenants, we assume that the EO-IDCN determines its provisioning strategy by optimizing the network-wide revenue gains, *i.e.*,

$$\mathcal{U} = \sum_{\mathcal{P}_{i,k} \in \psi} y_i \cdot c_{i,k}, \quad (5)$$

where y_i indicates whether the EO-IDCN admits the service of r_i.

III. Mixed-Strategy Game-Theoretic Approach

A. Game Modeling

The problem of incentive-driven VNF-SC provisioning essentially can be modeled as a noncooperative game, *i.e.*, tenant game, where tenants act as players and try to maximize their profits by selecting the most appropriate provisioning schemes (*i.e.*, strategies). We apply the Nash equilibrium (NE) method, which is one of the most important tools for noncooperative games, for analyzing the tenant game. Conceptually, NE of a game refers to strategy profiles with which no player can increase its profit by unilaterally deviating from them. Specifically for the tenant game, a strategy profile ψ^* is a pure-strategy NE if and only if for any provisioning scheme $\mathcal{P}_{i,k} \in \psi^*$,

$$U_{i,k}^{(\psi^*)^{-i}} \geq U_{i,j}^{(\psi^*)^{-i}}, \forall j \neq k. \quad (6)$$

TABLE I
Tenant profits under different strategy profiles.

(U_1, U_2) ψ_2 / ψ_1	$\mathcal{P}_{2,1}$	$\mathcal{P}_{2,2}$
$\mathcal{P}_{1,1}$	$(80, 80)$	$(80, 140)$
$\mathcal{P}_{1,2}$	$(140, 80)$	$(60, 60)$

Let us continue with the example in Fig. 2 and assume that $\beta_1 = \beta_2 = 100$, $c_{1,1} = c_{2,1} = 60$ (labeled by solid lines), $c_{1,2} = c_{2,2} = 30$, $\phi_1(b_1) = \phi_2(b_2) = 4$, $\tau_i + l_{i,k} = 1/6$ and $\varsigma_{n,m} = 10, \forall i, k, n, m$, we can calculate tenant profits under different strategy profiles in Table I and easily verify with Eq. 6 that $\{\mathcal{P}_{1,1}, \mathcal{P}_{2,2}\}$ and $\{\mathcal{P}_{1,2}, \mathcal{P}_{2,1}\}$ are the two pure-strategy NE of the game. However, these equilibrium points actually can hardly be achieved in noncooperative operations as they are always biased to one of the tenants. Moreover, it is often difficult to calculate or even prove the existence of pure-strategy NE, especially for the case when the strategy space is discrete as in our problem [23].

On the other hand, mixed-strategy gaming, where players select game strategies with certain probability distributions, provides a more practical insight for designing incentive-driven VNF-SC provisioning paradigms. Specifically, let $x_{i,k} \in [0, 1]$ denote the probability with which r_i selects $\mathcal{P}_{i,k}$, we can model a mixed-strategy game as,

$$\max_x \quad U_i(x) = \sum_{\mathcal{P}_{i,k}} x_{i,k} \sum_{\psi^{-i}} \left(U_{i,k}^{\psi^{-i}} \prod_{\mathcal{P}_{t,j} \in \psi^{-i}} x_{t,j}\right), \forall r_i \quad (7)$$

$$\text{s.t.} \quad \sum_{\mathcal{P}_{i,k}} x_{i,k} = 1, \quad (8)$$

where $U_i(x)$ is the expected profit of r_i. Similarly, we can study the game by looking into the mixed-strategy Nash equilibrium (MSNE), which is defined as,

$$U_i(x^*) \geq U_i\left(x_i, (x^*)^{-i}\right), \forall r_i, x_i \neq x_i^*, \quad (9)$$

where $(x^*)^{-i} = x^* \setminus x_i^*$. Let $\mathcal{S}_i = \{\mathcal{P}_{i,k}, \forall x_{i,k} > 0\}$ and $U_{i,k}(x) = \sum_{\psi^{-i}} \left(U_{i,k}^{\psi^{-i}} \prod_{\mathcal{P}_{t,j} \in \psi^{-i}} x_{t,j}\right)$, the following conditions for MSNE then can be deduced,

$$U_{i,k}(x^*) = U_{i,j}(x^*), \quad \forall \mathcal{P}_{i,k}, \mathcal{P}_{i,j} \in \mathcal{S}_i. \quad (10)$$

Eq. 10 actually implies that every provisioning scheme that tenants select with non-zero probabilities has the same profit expectation. This is because if there exists any provisioning scheme belonging to $\mathcal{S}_i$ that is with a different profit expectation, then provisioning schemes with lower profits will definitely be assigned zero probabilities according to Eq. 7, which is in conflict with the definition of the support set $\mathcal{S}_i$.

[1] According to the M/M/1 model, the average time a job stays in the system equates to $1/(\mu - \lambda)$, where μ is the processing rate of the server and λ is the arrival rate of the queue.

Algorithm 1: Iterated Dominance Approach.

```
set 𝒮 = 𝒫, Ŝ = ∅;
while 𝒮 ≠ Ŝ do
    Ŝ = 𝒮;
    for each r_i do
        get all ψ^{-i} with 𝒮;
        calculate max_x U_{i,k}(x) and min_x U_{i,k}(x), ∀𝒫_{i,k} ∈ 𝒮_i;
        delete 𝒫_{i,j} from 𝒮_i if
            max_x U_{i,j}(x) ≤ min_x U_{i,k}(x), ∃𝒫_{i,k};
    end
end
```

One good property of mixed-strategy gaming is that every game with a finite number of players and strategy space is ensured to have at least one MSNE [24]. Formally, we can calculate these MSNE by applying the iterated dominance approach [25] in *Algorithm* 1 and solving Eqs. 8 and 10. Recall the example in Fig. 2 and the assumptions made for Table I, we first obtain two support sets, each containing two provisioning schemes, as neither of the two schemes of each request can dominant the other one. For example, $U_{1,1}(x) > U_{1,2}(x)$ when $x_{2,1} < 0.25$ and otherwise, $U_{1,1}(x) \leq U_{1,2}(x)$. Then, by solving the equation set (1) $80 \cdot x_{2,1} + 80 \cdot x_{2,2} = 140 \cdot x_{2,1} + 60 \cdot x_{2,2}$, (2) $80 \cdot x_{1,1} + 80 \cdot x_{1,2} = 140 \cdot x_{1,1} + 60 \cdot x_{1,2}$, (3) $x_{1,1} + x_{1,2} = 1$ and (4) $x_{2,1} + x_{2,2} = 1$, we compute the MSNE as $x_{1,1} = x_{2,1} = 0.25$ and $x_{1,2} = x_{2,2} = 0.75$. Note that, since each equation yielded from Eq. 10 contains multiple terms of the production of decision variables, *i.e.*, $U_{i,k}^{\psi^{-i}} \prod_{\mathcal{P}_{t,j} \in \psi^{-i}} x_{t,j}$, the problem of calculating MSNE becomes intractable when the number of requests is larger than three [26]. Therefore, in this work, we aim to design time-efficient heuristic algorithms to assist tenants in finding approximate equilibrium solutions, and the detail of the design will be presented in the next section.

B. Heuristic Algorithm

We first introduce an auxiliary graph (AG) that facilitates the algorithm design. Fig. 3(a) shows an example of the AG. In particular, each node in the AG represents a provisioning scheme, and two nodes are connected if the corresponding provisioning schemes share the processing of the same VNFs in the same DCs. Note that, we do not connect two nodes that belong to the same request. Each node is assigned a weight that is equal to the expected profit of the provisioning scheme, *i.e.*, $U_{i,k}(x)$. With the AG, the basic idea of our heuristic design is to iteratively adjust the probability of each provisioning scheme so as to approximate the conditions for MSNE defined by Eq. 10. *Algorithm* 2 shows the detailed procedures for calculating approximate MSNE for the game. First of all, *Lines* 1-3 are for initialization, where we calculate the support set $\mathcal{S}$, construct an AG based on the provisioning schemes in it and set a uniform initial probability distribution. The while-loop covering *Lines* 4-24 corresponds to the iterative optimization process, consisting of multiple optimization episodes (the for-loop from *Line* 5 to 20, where θ_0 is a preset parameter).

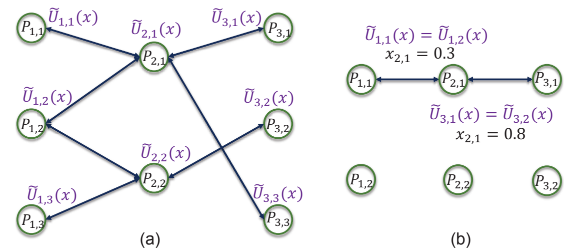

Fig. 3. Examples for (a) AG and (b) the case when MSNE does not exist.

Specifically, within each episode, *Line* 6 first calculates the estimated profit expectation of each provisioning scheme as,

$$\tilde{U}_{i,k}(x) = \frac{\beta_i - c_{i,k}}{\tau_i + l_{i,k} + \sum\limits_{n \in V_D} \sum\limits_{m \in \Theta_n} \frac{g_{i,k}^{n,m}}{\varsigma_{n,m} - \phi_i(b_i) - \tilde{\varsigma}_{n,m}^{i}(x)}}, \forall \mathcal{P}_{i,k}, \tag{11}$$

where

$$\tilde{\varsigma}_{n,m}^{i}(x) = \sum_{\mathcal{P}_{t,j} \in \mathcal{S} \setminus \mathcal{S}_i} x_{t,j} \cdot g_{t,j}^{n,m} \cdot \phi_t(b_t), \tag{12}$$

is the expected VNF capacity usage in each DC by provisioning schemes from $\mathcal{S} \setminus \mathcal{S}_i$. The reason why we adopt $\tilde{U}_{i,k}(x)$ is that calculating the exact values of profit expectations involves enumerating all possible game outcomes (*i.e.*, ψ, see Eq. 7) whose complexity will increase exponentially with the scale of the problem. *Line* 7 calculates the mean value of $\tilde{U}_{i,k}(x)$ for each request as $\mathcal{A}_i$. Then, for each provisioning scheme, *Lines* 12-18 compare $\tilde{U}_{i,k}(x)$ with $\mathcal{A}_i$ and increase/decrease the probabilities of all its adjacent nodes in the AG if $\tilde{U}_{i,k}(x)$ is larger/smaller than $\mathcal{A}_i$. Here, the step sizes of adjusting probabilities are adapted based on the distances with the equilibrium point, *i.e.*, $\left|\tilde{U}_{i,k}(x) - \mathcal{A}_i\right| = 0, \forall \mathcal{P}_{i,k}$, and ϵ_0 and α_0 are both parameters. *Line* 19 is for normalization. Note that, the iterated dominance approach in *Algorithm* 1 does not necessarily generate a support set that ensures the convergence of our optimization method. Take the AG in Fig. 3(b) as an example, where all the six provisioning schemes are included in $\mathcal{S}$ initially. However, in order to make $\tilde{U}_{1,1}(x) = \tilde{U}_{1,2}(x)$ and $\tilde{U}_{3,1}(x) = \tilde{U}_{3,2}(x)$, $x_{2,1}$ has to be set as 0.3 and 0.8, respectively, which is obviously contradictory. In fact, no MSNE exists with such a support set. Therefore, in *Line* 21, if the algorithm cannot converge after an optimization episode, we adjust $\mathcal{S}$ by deleting the provisioning scheme that has the largest profit difference with the best scheme of the same request from it [2]. The rationale behind this operation is that by preferentially removing provisioning schemes with lower profits, we can potentially generate an equilibrium solution with higher request profit. With *Lines* 22-23, the algorithm recalculates the support set and normalizes the probabilities to prepare for the next optimization episode. Finally, as shown by *Lines* 8-11, the algorithm converges when the maximum profit difference among provisioning schemes of every request is lower than a preset threshold η_0 (*e.g.*, 0.5%). The complexity of *Algorithm* 2 is $O\left(\theta_0 |V| |\Theta| |\mathcal{P}|^3\right)$, where $\Theta = \bigcup_{n \in V_D} \Theta_n$.

[2]To get the optimal support set, we need to check all the subsets of $\mathcal{S}$ which is impractical when the scale of the problem is large. Therefore, we focus on designing heuristic approaches in this work

Algorithm 2: Procedures of Calculating Approximate MSNE.

calculate $\mathcal{S}$ with *Algorithm* 1;
construct an AG based on $\mathcal{S}$;
set $x_{i,k} = 1/\left|\mathcal{S}_i\right|, \forall \mathcal{P}_{i,k} \in \mathcal{S}$;
while 1 **do**
  for $\theta = 1 : \theta_0$ **do**
    calculate $\tilde{U}_{i,k}(x), \forall \mathcal{P}_{i,k} \in \mathcal{S}$ with Eqs. 11-12;
    calculate $\mathcal{A}_i = \frac{\sum_{\mathcal{P}_{i,k} \in \mathcal{S}_i} \tilde{U}_{i,k}(x)}{|\mathcal{S}_i|}, \forall r_i$;
    calculate $\eta_i = \max\limits_{\mathcal{P}_{i,k} \in \mathcal{S}_i} \frac{\left|\tilde{U}_{i,k}(x) - \mathcal{A}_i\right|}{\mathcal{A}_i}, \forall r_i$;
    if $\eta_i \leq \eta_0, \forall r_i$ **then**
      return;
    end
    for *each* $\mathcal{P}_{i,k} \in \mathcal{S}$ **do**
      if $\tilde{U}_{i,k}(x) > \mathcal{A}_i$ **then**
        set $x_{t,j} = x_{t,j} + \epsilon_0 \alpha_0^{\frac{\left|\tilde{U}_{i,k}(x) - \mathcal{A}_i\right|}{\mathcal{A}_i}}$ for each adjacent node $\mathcal{P}_{t,j}$ of $\mathcal{P}_{i,k}$ in the AG;
      else if $\tilde{U}_{i,k}(x) < \mathcal{A}_i$ **then**
        set $x_{t,j} = \max\left\{0, x_{t,j} - \epsilon_0 \alpha_0^{\frac{\left|\tilde{U}_{i,k}(x) - \mathcal{A}_i\right|}{\mathcal{A}_i}}\right\}$ for each adjacent node $\mathcal{P}_{t,j}$ of $\mathcal{P}_{i,k}$ in the AG;
      end
    end
    set $x_{i,k} = \frac{x_{i,k}}{\sum_{\mathcal{P}_{t,j} \in \mathcal{S}_i} x_{t,j}}, \forall \mathcal{P}_{i,k} \in \mathcal{S}$;
  end
  delete $\mathcal{P}_{i,k} = \arg\max\limits_{\mathcal{P}_{t,j}} \left\{ \frac{\max\left\{\tilde{U}_{t,j'}(x), \forall \mathcal{P}_{t,j'} \in \mathcal{S}_t\right\} - \tilde{U}_{t,j}(x)}{\max\left\{\tilde{U}_{t,j'}(x), \forall \mathcal{P}_{t,j'} \in \mathcal{S}_t\right\}} \right\}$ from $\mathcal{S}$;
  set $\mathcal{P} = \mathcal{S}$, recalculate $\mathcal{S}$ with *Algorithm* 1 and update the AG accordingly;
  set $x_{i,k} = \frac{x_{i,k}}{\sum_{\mathcal{P}_{t,j} \in \mathcal{S}_i} x_{t,j}}, \forall \mathcal{P}_{i,k} \in \mathcal{S}$;
end

IV. Dynamic Resource Pricing

The design of tenant game in Section III motivates tenants to use VNFs with higher residual processing capacities (thus lower latencies), facilitating more balanced IT resource utilizations across DCs. On the other hand, as the tenants have neither the knowledge about network topology and spectrum utilization nor the incentive to use network resources in a more reasonable way, their decisions may lead to severer resource bottlenecking or spectrum fragmentation and thus result in decreased network throughput. Therefore, in this work on EO-IDCNs, we propose a dynamic resource pricing strategy that can regulate the network resource utilization by affecting tenants behaviors.

The dynamic pricing strategy sets the unit prices for per FS and O/E/O usages per provisioning period (*i.e.*, $p^e_{FS}, \forall e \in E$ and $p^n_{OEO}, \forall n \in V_D$ respectively) in real-time according to the actual network status. Specifically, the optimal prices can be determined by solving the following optimization problem that maximizes the network-wide profit.

$$\max \quad \mathcal{U} = \sum_{\mathcal{P}_{i,k} \in \psi} y_i \cdot c_{i,k}, \tag{13}$$

where y_i has the same definition with that in Eq. 5 and,

$$c_{i,k} = \left(\sum_{e \in E} p^e_{FS} \sum_{f \in [1,F]} z^{e,f}_{i,k} + \sum_{n \in V_D} \pi^n_{i,k} \cdot p^n_{OEO} + \chi^{i,k}_{IT} \cdot p_{IT} \right) \cdot T_i, \tag{14}$$

where $z^{e,f}_{i,k}$ and $\pi^n_{i,k}$ are boolean variables indicating the spectrum and O/E/O allocations for $\mathcal{P}_{i,k}$ if it is selected by r_i, *i.e.*, $z^{e,f}_{i,k}$ and $\pi^n_{i,k}$ equate to 1 if the f-th FS on link e or an O/E/O in node n is allocated. The resource constraints are,

$$\sum_{\mathcal{P}_{i,k} \in \psi} y_i \cdot z^{e,f}_{i,k} \leq 1, \forall e \in E, f \in [1, F], \tag{15}$$

$$\sum_{\mathcal{P}_{i,k} \in \psi} y_i \cdot \pi^n_{i,k} \leq M_n, \forall n \in V_D, \tag{16}$$

$$\sum_{\mathcal{P}_{i,k} \in \psi} y_i \cdot g^{n,m}_{i,k} \cdot \phi_i(b_i) < \varsigma_{n,m}, \forall n \in V_D, m \in \Theta_n, \tag{17}$$

where M_n is the number of available O/E/O in node n.

Nevertheless, solving Eqs. 13-17 requires calculating ψ for every possible pricing strategy, which makes the problem intractable. Hence, we propose to realize dynamic pricing with a simple μ^0-percentile resource utilization based heuristic approach in this work. In particular, let $\mu^n_{OEO}, \forall n \in V_D$ denote the O/E/O utilization ratio in node n, the EO-IDCN sets p^n_{OEO} as,

$$p^n_{OEO} = \begin{cases} p^0_{OEO}, & \mu^n_{OEO} < \mu^0_{OEO}, \\ p^0_{OEO} \left(1 + \varepsilon_0 \left(\mu^n_{OEO} - \mu^0_{OEO}\right)^{\sigma_0}\right), & \mu^n_{OEO} \geq \mu^0_{OEO}, \end{cases} \tag{18}$$

where p^0_{OEO} is the base price, ε_0 and σ_0 are positive parameters. Note that, usually σ_0 should be set larger than 1 so that p^n_{OEO} increases faster as μ^n_{OEO} goes up closer to 100%. The situation for determining $p^e_{FS}, \forall e \in E$ is more complicated as we need to consider not only the FS utilization ratio but also the sizes of available FS-blocks due to the unique spectrum allocation mechanism in EONs, *e.g.*, spectrum continuity and contiguity constraints [27]–[29]. Instead of using p^e_{FS}, we make the EO-IDCN price the FS usage for each provisioning scheme $\mathcal{P}_{i,k}$ separately, *i.e.*,

$$p^{i,k}_{FS} = \begin{cases} p^0_{FS}, & \mu^{i,k}_{FS} < \mu^0_{FS}, \\ p^0_{FS} \left(1 + \hat{\varepsilon}_0 \left(\mu^{i,k}_{FS} - \mu^0_{FS}\right)^{\hat{\sigma}_0}\right), & \mu^{i,k}_{FS} \geq \mu^0_{FS}, \end{cases} \tag{19}$$

where $\hat{\varepsilon}_0$ and $\hat{\sigma}_0$ are positive parameters, and $\mu^{i,k}_{FS}$ is calculated as,

$$\mu^{i,k}_{FS} = 1 - \sum_h \left(\frac{\mathcal{F}_h}{F}\right)^{\hat{\delta}_0}, \tag{20}$$

where $\mathcal{F}_h$ is the size of the h-th available FS-block on $\mathcal{P}_{i,k}$ and $\hat{\delta}_0 > 1$ is a parameter to differentiate the weights of FS-blocks with different sizes. Eq. 20 in fact takes into account the impact of spectrum fragmentation. For instance, a service path with large number of small pieces of available spectra is associated with a large $\mu^{i,k}_{FS}$ (thus high $p^{i,k}_{FS}$) although the actual spectrum utilization ratio is only moderate.

V. Simulation Results

We evaluate the performance of the proposed game-theoretic approaches with numerical simulations in this section and Table II summarizes the simulation setup.

A. Static Network Planning

We first conduct static network planning simulations to investigate the behaviors of tenants. In the simulations, the processing capacity of each type of VNF (*i.e.*, $\varsigma_{n,m}$) is set as 1800 units, each tenant receives 10 provisioning schemes from the broker and its budget β_i is given based on the estimation of the resource consumption cost on the longest service path. Note that, since all the requests are known in advance and served simultaneously in static network planning problems, we do not incorporate the designed dynamic resource pricing strategy in the simulations and the unit prices for IT, FS and O/E/O usages are set to be equal to $\left\{p_{IT}, p^0_{FS}, p^0_{OEO}\right\}$ which are given by Table II. The baseline algorithms are VNF-SC-LC and VNF-SC-Random, where each tenant selects the provisioning scheme with the least resource cost or randomly, while our proposed game-theoretic approach is denoted as VNF-SC-Game.

TABLE II
Simulation setup.

$G(V, E)$	14-node NSFNET Topology [29]
V_D	{1,4,6,7,9,11,14}
Θ_n	{VNF-1,VNF-2,...,VNF-6}
$\{F, M_n\}$	$\{350, 40\}$
Traffic Model	Uniform & Poisson
$\phi_i(b_i) = b_i$	$[25, 250]$ Gb/s
$\|\Gamma_i\|$	2
τ_i	$[0.01, 0.10]$ sec
$\{\theta_0, \eta_0, \epsilon_0, \alpha_0\}$	$\{300, 0.5\%, 0.008, 20\}$
$\left\{p_{IT}, p^0_{FS}, p^0_{OEO}\right\}$	$\{1, 5, 25\}$ units
$\left\{\mu^0_{OEO}, \varepsilon_0, \sigma_0\right\}$	$\{80\%, 35, 1\}$
$\left\{\mu^0_{FS}, \hat{\varepsilon}_0, \hat{\sigma}_0, \hat{\delta}_0\right\}$	$\{50\%, 5, 2, 2\}$

Fig. 4(a) shows the results on average request profit achieved by tenants, and we can see that VNF-SC-Game outperforms both VNF-SC-LC and VNF-SC-Random while the profits from VNF-SC-Random are the lowest. Meanwhile, the advantage from VNF-SC-Game gets larger when the number of requests increases. The rationale behind this is that the proposed game-theoretic approach assists tenants to intelligently select provisioning schemes that achieve the best balance between the resource consumption cost and service latency, which is especially critical when the EO-IDCN becomes more saturated (the service latencies become more sensitive the changes of residual VNF processing capacities when they approach 0 according to Eq. 3). The above analysis can be verified by the results on average service latency and resource consumption cost shown in Figs. 4(b) and 4(c), respectively. We can observe that VNF-SC-Game always achieves the lowest service latencies among the three algorithms and only slightly higher resource consumption costs than VNF-SC-LC. As expected, the service latencies from VNF-SC-LC increase rapidly with the number of requests. The performance of VNF-SC-Random is much worse than those of the rest algorithms due to its frequent use of long-distance and congested service paths. Fig. 4(d) plots the results on the maximum VNF capacity utilization ratio in the EO-IDCN, which further consolidate the analysis. It can be seen that VNF-SC-Game facilitates the most balanced utilization of VNFs, while the maximum utilization from VNF-SC-LC can reach as high as 95%. This implies that VNF-SC-LC may incur resource collisions among requests (thus service blocking) when we further increase the traffic load, clearly demonstrating the disadvantage of VNF-SC-LC. Also notice that, the fixed strategy used by VNF-SC-LC is actually not a stable solution in real network operations as one tenant can easily recognize this strategy from its competitors and improve its profit by switching to a better strategy. We also conduct simulations with different $\varsigma_{n,m}$ setup, with which we can observe the similar trends as those discussed above.

TABLE III
Results on the convergence of VNF-SC-Game ($|\mathcal{R}| = 100$).

$\varsigma_{n,m}$	2200	2000	1800	1600	1400
Iterations to Converge	9600	37200	73800	94800	111300

We then study the convergence of VNF-SC-Game and Table III shows the numbers of iterations (*i.e.*, iterations that *Lines* 5-20 of *Algorithm* 2 are executed) needed for the algorithm to converge. We can see that more iterations are required when we reduce $\varsigma_{n,m}$, which is because provisioning schemes with higher resource consumption costs are less likely to be dominated when service latencies begin to play a more important role in deciding the tenant profits, resulting in a larger support set $\mathcal{S}$ for the algorithm to optimize with. Note that, the performance of VNF-SC-Game is also associated with other parameters such as θ_0 and η_0, and the selections of these parameters (as depicted in Table II) are already the optimized ones according to our extensive simulations.

B. Dynamic Service Provisioning

Next, we perform dynamic service provisioning simulations where VNF-SC requests can come and go on-the-fly. The processing capacities of VNFs range from 3000 to 3500 units, and the number of provisioning schemes each tenant receives is still 10. We compare the performance of VNF-SC-Game with dynamic pricing (namely, VNF-SC-Game-DP) with those of approaches leveraging fixed pricing, *i.e.*, VNF-SC-Game-FP, VNF-SC-LC-FP and VNF-SC-Random-FP. For approaches with fixed pricing, the pricing rate is set as 2.1, *i.e.*, the unit prices for IT, FS and O/E/O usages equate to $2.1 \times \left\{p_{IT}, p^0_{FS}, p^0_{OEO}\right\}$. Also, different from that in network planning simulations, the budget of each request is set based on the pricing rate being equal to 2.0. Fig. 5(a) shows the results on request blocking probability, where we can observe that VNF-SC-Game achieves significant lower blocking probability than VNF-SC-LC and VNF-SC-Random. Meanwhile, with the designed dynamic pricing strategy, $2.4\times$ in average blocking reduction is further achieved by VNF-SC-Game. This is because our proposed game-theoretic approach as well as the dynamic pricing strategy make tenants use network and IT

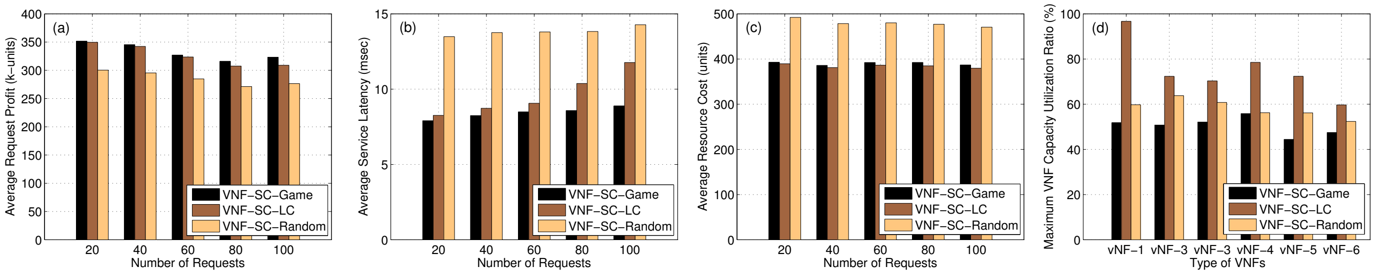

Fig. 4. Results for static network planning simulations, (a) average request profit, (b) average end-to-end service latency, (c) average resource consumption cost, and (d) maximum VNF capacity utilization ratio in the EO-IDCN.

resources in a more balanced way, thus effectively relieving the impacts from resource bottlenecking. We also measure the profits achieved by the EO-IDCN and tenants when the traffic load is 500 erlangs with different pricing rate setup for fixed pricing based approaches, and Figs. 5(b) and 5(c) show the corresponding simulation results. Firstly, we observe that among the approaches with fixed pricing, VNF-SC-Game always achieves both the highest network (EO-IDCN) and request profits. Being consistent with the results in Fig. 4(a), the average request profit from VNF-SC-Random is the lowest. Secondly, as expected, the network profits achieved by fixed pricing based approaches go up monotonously with the pricing rate while the results on request profit exhibit the opposite trend. The network profit from VNF-SC-Game-FP is still slightly lower than that from VNF-SC-Game-DP when the pricing rate is 2.1, while the request profit from it at this moment has been lower than that from VNF-SC-Game-DP. Note that, we do not evaluate the cases when the pricing rate is higher than 2.1 as we need to ensure the resource consumption cost of each request is within its budget. We also perform simulations with different parameter setup, *e.g.*, $\varsigma_{n,m}$ and M_n, and the results confirm our previous conclusion that the advantage from the proposed game-theoretic approach gets more distinct when the resource capacity constraints are tighter.

VI. Conclusion

In this paper, we proposed an incentive-driven VNF-SC provisioning framework for broker-based EO-IDCNs. We modeled the problem as a noncooperative mixed-strategy game, where tenants compete for VNF-SC provisioning services. An AG-based heuristic algorithm was developed for tenants to efficiently compute approximate equilibrium solutions in the games. We also designed a dynamic resource pricing strategy for EO-IDCNs as a complementary method to the game-theoretic approach. Simulation results showed that the proposed game-theoretic approach could facilitate both higher tenant and network-wide profits and improve the network throughput as well, while the dynamic pricing strategy further reduced the request blocking probability with a factor of $\sim 2.4\times$.

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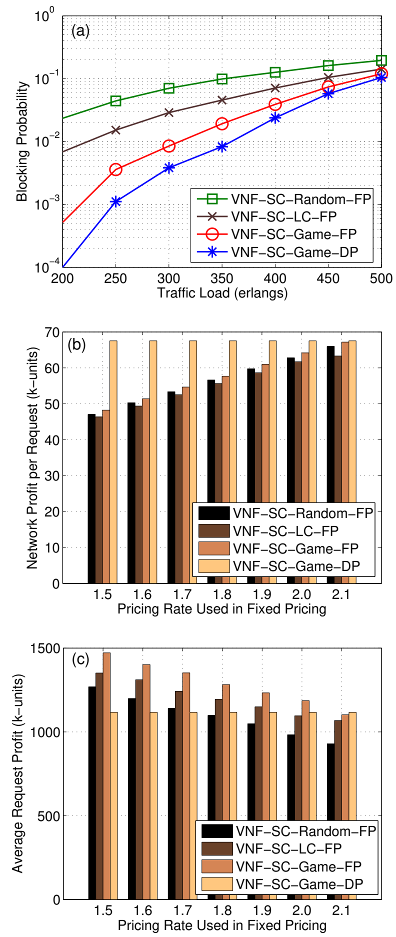

Fig. 5. Results for dynamic service provisioning simulations, (a) request blocking probability, (b) network profit from per request and (c) average request profit.

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