# On Efficient Incentive-Driven VNF Service Chain Provisioning with Mixed-Strategy Gaming in Broker-based EO-IDCNs

**Xiaoliang Chen[1], Lu Sun[2], Zuqing Zhu[2], Hongbo Lu[1], S. J. B. Yoo[1]**

*1. University of California, Davis, Davis, CA 95616, USA, Email: xlichen@ucdavis.edu, sbyoo@ucdavis.edu*
*2. University of Science and Technology of China, Hefei, Anhui 230027, China, Email: zqzhu@ieee.org*

**Abstract:** We propose to realize incentive-driven virtual network function service chain provisioning in broker-based elastic optical inter-datacenter networks with mixed-strategy gaming and design a heuristic to find the near-equilibrium solutions. Simulation results verify both the effectiveness and stability of the proposed approach.

**OCIS codes:** (060.1155) All-optical networks; (060.4251) Networks, assignment and routing algorithms.

## 1. Introduction

The emerging of network function virtualization (NFV) [1] together with software-defined networking (SDN) boosts the revolution of computing networks to a new climax. By replacing proprietary hardware elements and deploying virtual network functions (VNFs) based on generic network and IT resources (*e.g.*, bandwidth and CPU *etc.*), NFV introduces unprecedented cost-efficiency and flexibility to the service provisioning in computing networks. Specifically, NFV can steer traffics through sequences of VNFs deployed in datacenters (DCs) to form service chains (SCs). Therefore, one of the key problems in NFV is how to facilitate efficient VNF-SC provisioning with cross-stratum (*i.e.*, transport networks and DCs) resource optimization. This is especially true when elastic optical networking is exploited for building the interconnection of DCs, *i.e.*, elastic optical inter-DC networks (EO-IDCNs), where the spectrum and VNF allocation schemes are much more sophisticated [2]. The authors of [3] discussed the control plane arrangement for EO-IDCNs and based on this architecture, Fang *et al.* studied the joint IT and spectrum assignment schemes for efficient VNF-SC provisioning in EO-IDCNs [4]. However, these existing studies only tried to optimize the resource allocation for network operators while failed to address the fairness among the end users. Moreover, most of them assumed a single decision-maker based top-down management of an EO-IDCN, which violates the autonomy of each administration domain and is hence unrealistic.

In this paper, we investigate how to realize user-defined (thus incentive-driven) VNF-SC provisioning in EO-IDCNs. We design a more realistic network architecture that leverages multiple brokers [5] to manage cross-stratum resource abstractions and to bridge end users and network/DC managers for facilitating incentive-driven VNF-SC provisioning. Then, we show that the problem is essentially a mixed-strategy noncooperative game where every user tries to maximize its profit by determining the most appropriate probability for each provisioning scheme to be used. An algorithm is then proposed to find the near-equilibrium solutions for the end users. Simulation results show that our game-theoretic proposal can realize VNF-SC provisioning that is not only cost-efficient but also stable.

## 2. Network Architecture

Fig. 1(a) depicts the proposed network architecture to facilitate incentive-driven VNF-SC provisioning in EO-IDCNs. The data plane is comprised of a set of DCs, each of which carries certain types of VNFs and locally attaches to an optical core node in the EO-IDCN. The brokers reside in the management plane to maintain cross-stratum resource abstractions and bridge end users and infrastructure managers to enable user-defined VNF-SC provisioning. Specifically, each broker first collects VNF-SC requests in its request pool, calculates a feasible provisioning scheme for each of them, and then broadcasts the results to the users. Next, each user specifies its preferred provisioning scheme to maximize its own profit, while the broker in turn informs the related managers about the users' decisions, which will

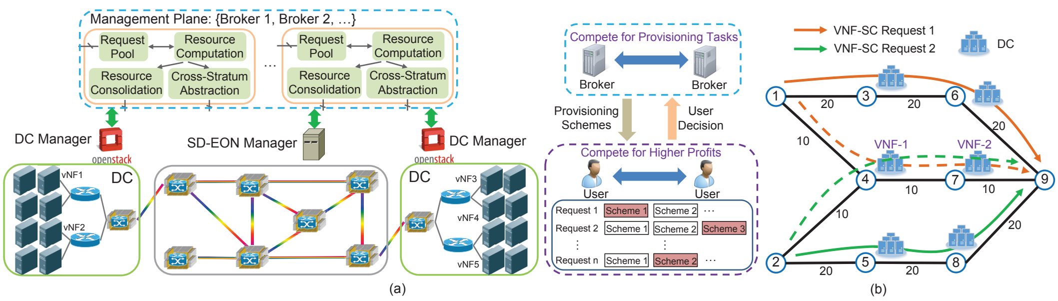


Fig. 1. (a) Network architecture of an EO-IDCN and (b) an example for profit-driven VNF-SC provisioning.

finally accomplish the corresponding lightpath and VNF configurations. Note that, the brokers may also compete with each other by developing more advanced provisioning strategies with predicting or learning capabilities to inspire more requests to use their services due to economic incentives. Fig. 1(b) shows an illustrative example for incentive-driven VNF-SC provisioning in EO-IDCNs. Each of the VNF-SC requests receives two service schemes, which are labeled by solid and dashed lines respectively. The numbers on the links indicate the costs of the schemes. It is interesting to notice that although both requests prefer the schemes marked in dashed lines due to smaller link costs, they might not choose the schemes unalterably because this would induce higher service latencies (thus costs) due to the sharing of VNFs.

## 3. Mixed-Strategy Gaming

We propose a mixed-strategy game-theoretic approach to realize incentive-driven VNF-SC provisioning in EO-IDCNs. Specifically, VNF-SC requests (*i.e.*, players) decide the probability for each scheme to be used (*i.e.*, strategies) in a noncooperative manner. The EO-IDCN topology is modeled as $G(V,E,V_D)$, where $V$ and $E$ are the sets of nodes and links in $G$, respectively, and $V_D$ ($V_D \subseteq V$) is the set of DCs which each attaches to an optical node locally. $\Theta$ represents all the types of VNFs instantiated in $V_D$, while $\Theta_n$ ($\Theta_n \subseteq \Theta$) indicates the set of VNFs available in DC $n$ ($n \in V_D$). We denote the set of VNF-SC requests as $\mathscr{R}\{r_i(s_i,d_i,\Gamma_i,b_i)\}$, where $s_i$ and $d_i$ are the source and destination nodes, $\Gamma_i$ contains the required VNF-SC and $b_i$ is the bandwidth demand in Gb/s. We also introduce the following notations: 1) $\mathscr{P}_i$, set of pre-calculated provisioning schemes for request $r_i$; 2) $c_{i,k}$, total cost on spectrum, transponder and IT resource usage from the $k$-th scheme of $r_i$, *i.e.*, $\mathscr{P}_{i,k}$; 3) $x_{i,k} \in [0,1]$, probability with which $r_i$ selects $\mathscr{P}_{i,k}$ as its provisioning scheme; 4) $\psi \in \Psi$, outcome of the game with $\psi_i \in \mathscr{P}_i$; 5) $\Psi^{-i}$, set of outcomes excluding the decision from $r_i$; 6) $\varsigma_{n,m}$, processing capability of VNF $m$ in DC $n$; and 7) $\sigma^{\psi}_{i,k}$, $\psi \in \Psi^{-i}$, boolean parameter which equals to 1 when there is resource collision to $r_i$ in outcome $\{\mathscr{P}_{i,k}\}\bigcup\psi$. Then, each request determines its gaming strategy $x_{i,k}$ by maximizing its expected profit, *i.e.*,

$$max \quad U_i = \sum_{\mathscr{P}_{i,k}} x_{i,k} \sum_{\psi\in\Psi^{-i}} \left(\prod_{\mathscr{P}_{t,j}\in\psi} x_{t,j}\right)\left(\frac{\beta_i}{D^{\psi}_{i,k}} - c_{i,k} - \sigma^{\psi}_{i,k}\cdot Q\right), \qquad s.t. \quad \sum_{\mathscr{P}_{i,k}} x_{i,k} = 1, \tag{1}$$

where $\beta_i/D^{\psi}_{i,k}$ is the reward that $r_i$ can get under the situation in which its service latency equals to $D^{\psi}_{i,k}$, and $Q$ is a positive value representing the penalty to $r_i$ when it encounters resource collision. Meanwhile, by modeling the processing of VNFs as $M/M/1$ queues, we can calculate $D^{\psi}_{i,k}$ as

$$D^{\psi}_{i,k} = l_{i,k} + \sum_{n\in V_D}\sum_{m\in\Theta_n} \frac{g^{n,m}_{i,k}}{\varsigma_{n,m} - b_i - \sum\limits_{\mathscr{P}_{t,j}\in\psi} g^{n,m}_{t,j}\cdot b_t}, \qquad s.t. \quad \varsigma_{n,m} - b_i - \sum_{\mathscr{P}_{t,j}\in\psi} g^{n,m}_{t,j}\cdot b_t > 0, \forall n,m \tag{2}$$

where $l_{i,k}$ is the propagation delay of $\mathscr{P}_{i,k}$, and $g^{n,m}_{i,k}$ is the boolean to indicate whether $\mathscr{P}_{i,k}$ uses VNF $m$ in DC $n$.

Due to the high complexity of calculating the Nash equilibrium for a mixed-strategy game with more than three players [6], we design a time-efficient heuristic to obtain approximate equilibrium solutions for the proposed gaming model and Table 3 describes the related operation principle. Basically, we are motivated by the essence of mixed-strategy Nash equilibria, *i.e.*, every player tries to make its competitors' profits indifferent whichever provisioning schemes belonging to the supports they chose, otherwise, they will simply chose schemes that bring the highest profits, which contradicts the definition of mixed-strategy gaming. Here, the support of a player contains all the provisioning schemes that are chosen with positive probabilities. In **Steps 1**-**3**, we calculate a few provisioning schemes for each VNF-SC request, find out the schemes that share VNFs and initiate each scheme with an equal probability. After obtaining the support for each request in **Step 4**, we proceed to iteratively adjust the probability of each scheme so as to reduce the profit difference among the schemes, *i.e.*, trying to approximate the equilibria (**Steps 5**-**7**). Finally, in the provisioning stage, each request selects a scheme based on the computed probability distribution, and when a resource collision happens, the broker randomly selects the requests to yield and then serves them subsequently.

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| **Step 1:** Calculate $K$ provisioning schemes for each VNF-SC request $r_i$. |
| **Step 2:** For each scheme $\mathscr{P}_{i,k}$ of $r_i$, find all the schemes from other requests that share same VNFs on same DCs with it and store them in $\mathscr{N}_{i,k}$. |
| **Step 3:** Initiate the probability of each scheme as $x_{i,k} = 1/K$, and calculate the maximum and expected profits that $r_i$ can achieve from $\mathscr{P}_{i,k}$ with Eqs. (1)-(2). |
| **Step 4:** For each $r_i$, store $\mathscr{P}_{i,k^*}$ which has the highest expected profit $U_{i,k^*}$ in its support $Sup_i$, and then add $\mathscr{P}_{i,k}$ whose maximum profit is no less than $U_{i,k^*}$ in $Sup_i$. Set $\mathscr{P}_i = \mathscr{P}_i - Sup_i$. |
| **Step 5:** Adjust each $x_{i,k}$ based on the expected profit, *i.e.*, $x_{i,k} = U_{i,k}/\sum U_{i,j}$. |
| **Step 6:** Recalculate each $U_{i,k}$, and set $x_{t,j} = x_{t,j} + \sigma, \forall \mathscr{P}_{t,j} \in \mathscr{N}_{i,k}$ if $U_{i,k} > \bar{U}_{i,k}$, otherwise set $x_{t,j} = x_{t,j} - \sigma$. |
| **Step 7:** Repeat **Steps 5-6** for $\delta$ times. |

Table 1. Operation principle of the proposed heuristic algorithm.

## 4. Performance Evaluation

We evaluate the performance of the proposed gaming approach (*namely*, VNF-SC-Game) with numerical simulations using the 14-node NSFNET topology in [2]. The benchmark algorithms are VNF-SC-LC and VNF-SC-Random, in which each VNF-SC request selects its provisioning scheme with the least resource cost or randomly, without considering the decisions from its competitors. We assume that there are in total 6 types of VNFs instantiated in DC nodes $\{1,4,6,7,9,11,14\}$, each of which has a capacity uniformly distributed within $[1800,2800]$ units, and each fiber link can accommodate 358 frequency slots (FS's). The bandwidth requirement of each request is randomly chosen from $[25,250]$ Gb/s, while the number of demanded VNFs is $1 \sim 2$. We set the unit costs of VNF, FS and optical transponder utilizations as 1, 10 and 50 units, respectively.

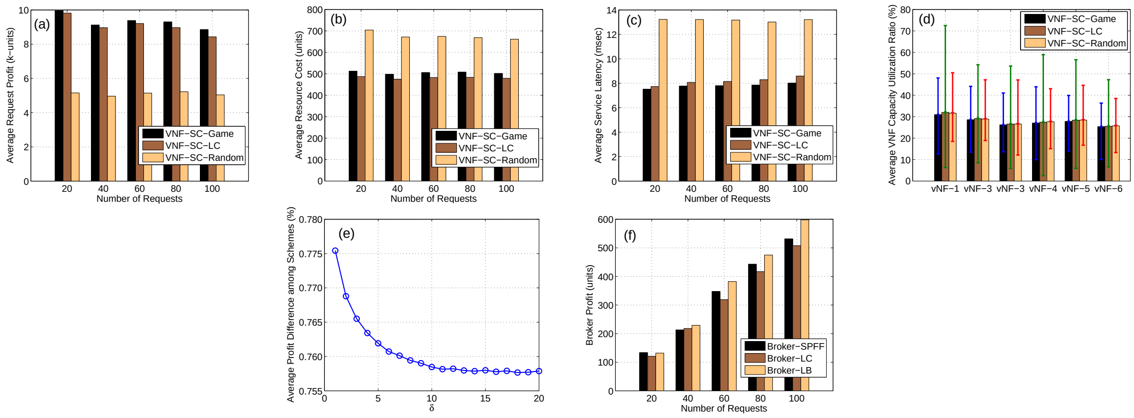


Fig. 2. Simulation results on (a) average request profit, (b) average resource cost, (c) average service latency, (d) average VNF capacity utilization ratio, (e) average profit difference among schemes within a request and (f) broker profit.

Fig. 2(a) shows the results on average request profit with $\sigma = 0.02$ and $\delta = 20$, and it can be seen that VNF-SC-Game outperforms VNF-SC-LC and VNF-SC-Random in all scenarios. This is because VNF-SC-Game can achieve the best balance between resource cost and service delay by intelligently adjusting the probability of each scheme to be used. The analysis can be verified with the results in Figs. 2(b)-(c), which indicate that although the average resource cost from VNF-SC-Game is slightly higher than that of VNF-SC-LC, the average service latency from it gets controlled well. As expected, the performance of VNF-SC-Random is always the worst due to using long and high-cost routing paths frequently. Note that, the results in Figs. 2(a)-(c) do not necessarily mean that the performance of VNF-SC-LC is comparable to that of VNF-SC-Game. The rationale behind this can be seen by analyzing the results in Fig. 2(d), which shows that VNF-SC-LC can cause severely imbalanced VNF usage, *i.e.*, utilization ratio ranging from less than 10% to even higher than 70%, while the situation in VNF-SC-Game is much better. More importantly, using a fixed provisioning strategy (as by VNF-SC-LC, unless it is a equilibrium strategy) is definitely unstable in noncooperative distributed systems, since other users can easily improve their profits by changing their strategies accordingly which is usually against the interest of the user itself. Therefore, we evaluate the performance of VNF-SC-Game in how much it can approach the equilibria. Fig. 2(e) shows the results on average profit difference among schemes within a request when the number of requests is 100, and we can observe that it converges quickly to as small as 0.758% with $\delta = 20$. Recall that the profit difference of each request in the equilibria is 0, the relatively good stability of VNF-SC-Game is hence verified. Finally, we compare the profit from three brokers in Fig. 2(f), which each calculates provisioning schemes for users with the shortest path and first-fit (SPFF), least cost (LC) or load balancing (LB) strategy and charges 5% above the resource costs as commissions for serving them. It can be seen that the three brokers achieve comparable profit with Broker-LB outperforming the rest ones, especially when the number of requests gets larger. This is because with VNF-SC-Game, users tend to diversify their provisioning schemes for realizing more balanced VNF utilizations, *i.e.*, lower service latencies, which is in consistent with the observations from Figs. 2(a)-(d).

## 5. Conclusion

We proposed to realize incentive-driven VNF-SC provisioning in broker-based EO-IDCNs with mixed-strategy gaming and designed a heuristic to obtain near-equilibrium solutions. Simulation results verified both the effectiveness and stability of the proposed gaming approach.

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