Incentive-Driven Bidding Strategy for Brokers to Compete for Service Provisioning Tasks in Multi-Domain SD-EONs

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***Abstract*—It is known that the multi-broker based management plane can potentially provide a realistic solution to facilitate incentive-driven cross-domain network orchestration in multi-domain software-defined elastic optical networks (SD-EONs). Such network orchestration assures the autonomy of each domain and supports economical service provisioning across multiple domains as well. In this work, we consider the economic principle in multi-broker based multi-domain SD-EONs and study how to realize incentive-driven service provisioning with broker competitions. We first present the theoretical model of the network operations to describe the noncooperative game in which the brokers compete for inter-domain provisioning tasks with only incomplete information on their competitors. Then, we analyze the Nash equilibrium in a simplified version of the game, and show that to maximize the brokers' profits in long-term repeated games, an effective bidding strategy is needed for the brokers to predict their competitors' behaviors and price their services in the optimal way. The bidding strategy is designed by leveraging the kernel density estimation scheme. Finally, to demonstrate the effectiveness of the proposed bidding strategy, we implement it in an OpenFlow-based multi-domain SD-EON control plane testbed. The experimental results verify that our system performs well and the brokers can obtain higher profits with the proposed bidding strategy in repeated games.**

***Index Terms*—Software-defined elastic optical networks (SD-EONs), Multi-broker, Noncooperative game, Nash Equilibrium.**

I. Introduction

INCENTIVE-driven brokers can promote higher performance, better resilience, and more efficient resource utilization in the future Internet that consists of many autonomous systems (AS's). Specifically, they are positioned in a higher network control and management (NC&M) level than the domain managers of AS's for coordinating the cross-domain operation. Since multiple brokers can compete/cooperate to realize cross-domain service provisioning, they respect the autonomy of each AS without dictating the top-down authoritative management [1]. Indeed, recent architectural study has shown the remarkable effectiveness of incentive-driven brokers in providing lower service latency and higher network throughput and availability [2], and the architecture has also been experimentally demonstrated in small scale inter-continental multi-domain software-defined networks (SDNs) [3]. Although the management plane with incentive-driven brokers can be effective in orchestrating heterogeneous AS's, *i.e.*, heterogeneous in terms of physical-layer technology (*e.g.*, wireless, wireline, optical and satellite), and in terms of network protocols and programmability [4, 5], its advantage in multi-domain software-defined elastic optical networks (SD-EONs) would potentially be more distinct.

SD-EONs combine the advantages from the programmability of SDNs and those from the efficient and flexible utilization of Tb/s network capacity by elastic optical networks (EONs). Specifically, EONs support super-channel and sub-wavelength switching with flexible spectrum allocation across a series of spectrally-contiguous frequency slots (FS's), and leverage advanced transmission techniques to optimize spectral efficiency [6, 7]. Meanwhile, SDN incorporates programmable centralized NC&M to undertake sophisticated spectrum management within a domain (or AS) [8–10]. As a result, SD-EONs can potentially realize adaptive, programmable, and application-aware ultra-high capacity networking with enhanced service support [11, 12]. Now, what is important is to design the NC&M architecture for facilitating efficient end-to-end service provisioning across multiple SD-EON domains, such that the distributed resources can be utilized effectively. To achieve this, we can use the hierarchical NC&M architecture that places an orchestrator on top of the domain managers. Unfortunately, this means that the orchestrator can dictate the entire multi-domain network, which is impractical when the domains are from different operators, causes survivability and scalability issues, and also violates the original (and successful) principle of autonomy in the Internet.

On the other hand, introducing a management plane with multiple incentive-driven brokers provides a not only powerful but also practical mechanism to operate the multi-domain SD-EONs that cover relatively large geographical areas. Specifically, the brokers offer services to the domain managers due to revenue profits and they may cooperate or compete with each other to avoid the drawbacks of a single orchestrator. Meanwhile, the incentive-driven nature of brokers also prompts them to apply more efficient provisioning schemes (*e.g.*, providing services with lower costs and higher availabilities) and more intelligent bidding strategies (*e.g.*, pricing their services more reasonably) so as to achieve higher revenue gains. This forms revenue-driven rational games which are similar to

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the cases in other commercial markets, and hence improves the performance of multi-domain service provisioning. Note that, as each broker has the abstracted global status of the multi-domain SD-EON, the competition/cooperation among them would result in relatively short latency and there is no need to worry about the convergence of routing calculation. This is the fundamental difference between our work and previous studies on game theory in the context of multi-domain optical networks [13, 14]. Recently, in [3], we conducted a preliminary study on how to assist the brokers in a multi-broker based multi-domain SD-EON to realize revenue-driven service provisioning, and formulated the competition among the brokers as a noncooperative game. However, the theoretical model in [3] was over-simplified, and thus the proposed bidding strategy did not fully address the problem from the perspective of the game theory.

In this paper, we extend our work in [3] to provide a more comprehensive analysis on the revenue-driven service provisioning framework in multi-broker based multi-domain SD-EONs. We first extend the theoretical model of the network operations to describe the noncooperative game among the brokers, *i.e.*, competing for inter-domain provisioning tasks with only incomplete information on each other. Then, we analyze the Nash equilibrium [15] in a simplified version of the game, and show that in order to maximize the brokers' profits in long-term repeated games, we need to design an effective bidding strategy with which the brokers can predict their competitors' behaviors and price their services in the optimal way. The bidding strategy is designed by leveraging the kernel density estimation scheme [16]. Finally, to demonstrate the effectiveness of the proposed bidding strategy, we implement it in an OpenFlow-based multi-domain SD-EON control plane testbed. The experimental results indicate that the system performs well and the brokers can obtain higher profits with the proposed bidding strategy in repeated games.

The rest of the paper is organized as follows. Section II surveys the related work briefly. We describe the theoretical model for the network operations in multi-broker based multi-domain SD-EONs in Section III. The proposed broker bidding strategy is laid out in Section IV. Section V discusses the system implementation for realizing the service provisioning competition in multi-broker based multi-domain SD-EONs, and the experimental results are presented and analyzed in Section VI. Finally, Section VII summarizes the paper.

II. Related Work

Previously, researchers have considered the service provisioning in multi-domain SD-EONs and demonstrated a few approaches to realize it [1–3, 11, 17–19]. Casellas *et al.* [17] demonstrated to manage a multi-domain SD-EON with an integrated path computation element (PCE) and OpenFlow controllers. In [11, 18], we studied how to realize efficient and collaborative resource allocation in OpenFlow-based multi-domain SD-EONs by making the OpenFlow controllers (OF-Cs) cooperate with each other in a peer-to-peer way. Note that, the studies mentioned above only considered a flat provisioning framework in which the domain managers (*e.g.*, OF-Cs) operate in a purely distributed way for inter-domain provisioning. However, due to the absence of centralized coordination among the domain managers, the purely distributed framework may result in relatively long protocol delay and information inconsistency, which would limit the performance on resource utilization and network scalability [20].

In order to address the issues with the flat provisioning framework, Marconett *et al.* [19] proposed a hierarchical framework by introducing a resource broker as the higher-level orchestrator in the management plane and using it to coordinate the domain managers for cross-domain network orchestration. The authors improved their proposal in [1, 2], and considered the multi-broker scenario, which was proven to be more realistic and robust, to realize revenue-driven cross-domain network orchestration. Note that, as the brokers may cooperate and/or compete with each other to maximize their profits, we need to design the optimal gaming strategy for them from the perspective of game theory. In [3], based on an over-simplified theoretical model, we designed a bidding strategy for the brokers to realize incentive-driven service provisioning.

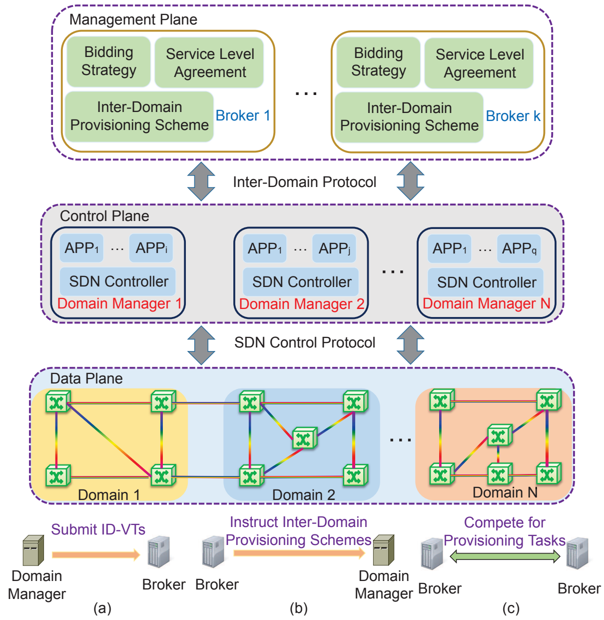


Fig. 1. Network architecture of a multi-broker based multi-domain SD-EON, and the actions (a) from domain managers to brokers, (b) from brokers to domain managers and (c) among brokers.

Game theory [15] has been widely used to optimize the operations of various networks. In [21], the authors investigated the problem of spectrum pricing in cognitive radio networks with a dynamic repeated game model, and proposed gaming strategies to overcome the inefficiency brought by Nash equilibrium. The cooperative spectrum sharing schemes for cognitive radio networks were studied in [22], using a game model in which each player only had incomplete information about their competitors. Kabranov *et al.* [23] addressed the routing and wavelength assignment (RWA) problem in fixed-grid wavelength-division multiplexing (WDM) networks and modeled it as a noncooperative game, in which multiple network operators could compete for lightpath services. A strategy was developed for the operators to adjust the price of wavelength resources adaptively. Under the assumption that RWA could be executed in a distributed and noncooperative way by each lightpath request, the authors of [24] modeled the RWA problem as a strategy game and analyzed the difference between the Nash equilibrium and the optimal solution.

The application of game theory in multi-domain optical networks was first addressed in [13], where the authors modeled the pricing of the advertised intra-domain information as a non-cooperative game and discussed the Nash and Pareto equilibrium for a few simple scenarios. However, neither impairment-aware routing and spectrum assignment [25, 26] nor the theoretical analysis on the Nash and Pareto equilibrium was presented. In [14], Guo *et al.* studied the game between the operators and customers in multi-domain optical networks, and by considering both the wavelength utilization and customers' satisfaction ratio on quality-of-transmission, the authors investigated the Nash equilibrium between the operators and customers and tried to improve their profits simultaneously. Nevertheless, the unique features related to multi-domain networks, *e.g.*, setting up inter-domain lightpaths cooperatively/noncooperatively, were not studied.

III. Multi-Broker based Service Provisioning Framework in Multi-Domain SD-EONs

A. Network Architecture

Fig. 1 shows a simplified schematic of the network architecture of a multi-broker based multi-domain SD-EON. The control and management planes consist of several domain managers (DMs) and multiple resource brokers. The NC&M of the multi-domain SD-EON operates in a hierarchical manner. In each domain, the DM controls the bandwidth-variable optical cross-connects (BV-OXCs) through an SDN controller (*e.g.*, OpenFlow controller (OF-C)) for intra-domain service provisioning. Meanwhile, it also subscribes to one or more brokers for inter-domain service provisioning. Hence, the brokers work as higher-level orchestrators to coordinate the DMs for cross-domain network orchestration.

Fig. 1 also illustrates the interactions among the DMs and brokers. According to the policies defined in their service-level agreements (SLAs), the DMs virtualize their intra-domain topologies for each broker, while the brokers help the DMs to establish inter-domain lightpaths. Hence, to provision an inter-domain lightpath, each broker has an abstracted view of the network, which includes the status of inter-domain links and the intra-domain virtual topologies (ID-VTs) from the DMs. An ID-VT consists of several border nodes (*i.e.*, BV-OXCs) and the virtual links (VLs) in between them. Specifically, the VLs are abstracted from the related intra-domain path segments. Note that, depending on the SLAs between them, a DM can submit different ID-VTs to different brokers. Meanwhile, different brokers can apply different inter-domain service provisioning schemes and bidding strategies to compete for the provisioning tasks.

B. Inter-Domain Service Provisioning Procedure

We use $G = \{G_i(V_i, E_i, BR_i)\}$ to model the multi-domain SD-EON, where $i \in [1, N]$ is the domain index, N is the number of domains, V_i and E_i are the sets of nodes and links[1] in domain G_i, respectively, and BR_i is the set of brokers that the DM in G_i subscribes to. $LR(s, d, B, T)$ denotes an inter-domain request, where s and d are the source and destination (*i.e.*, $s \in V_i, d \in V_j, i \neq j$), B is the bandwidth requirement in Gb/s, and T is the requested service duration.

Algorithm 1 shows the procedure to provision LR. As shown in *Line* 1, upon receiving an inter-domain request LR, the DM of the source domain (*e.g.*, DM-i in domain G_i) forwards the request's information to all the brokers that it subscribes to. Then, each broker collects ID-VTs from all the DMs, as shown in *Line* 4. Here, each ID-VT should consist of the VLs of the related intra-domain path segments, which are s to edge node(s), edge node(s) to edge node(s), and edge node(s) to d for the source, intermediate and destination domains, respectively. Meanwhile, all or some of the available frequency slots (FS's) on the path segments should also be included in the ID-VT [11]. With the ID-VTs, each broker calculates a provisioning scheme (*i.e.*, a routing, modulation and spectrum assignment (RMSA)) for LR in *Line* 5. If a feasible provisioning scheme can be found, the broker determines the price for it and submits the price to DM-i for bidding the task of provisioning LR, as shown in *Lines* 6-9. Finally, in *Lines* 14-15, DM-i selects the broker with the lowest price as the winner to provision LR, and then, the winning broker coordinates related DMs to set up LR.

Algorithm 1: Procedure for Provisioning Inter-Domain Lightpaths Originating from Domain G_i

1 **for** *each* $LR(s, d, B, T), s \in V_i$ **do**
2   DM-i forwards LR to all the brokers in BR_i;
3   **for** *each broker in* BR_i **do**
4   collect ID-VTs from all the DMs;
5   calculate a provisioning scheme for LR with the acquired information;
6   **if** *a feasible scheme can be obtained* **then**
7   price the inter-domain provisioning scheme;
8   submit the price to DM-i for bidding LR;
9   **end**
10   **end**
11   **if** *DM-i does not receive a bid* **then**
12   mark LR as blocked;
13   **else**
14   DM-i selects the broker with the lowest price as the winner to provision LR;
15   winning broker coordinates related DMs to set up the inter-domain lightpath for LR;
16   **end**
17 **end**

[1]Here, *w.o.l.g.*, we assume that each inter-domain link belongs to one and only one domain.

C. Game Model for Broker Competition

The inter-domain provisioning procedure mentioned in the previous subsection can be modeled as a noncooperative game, in which the brokers are the player and their pricing strategies for bidding the provisioning tasks are the game strategies. Basically, after obtaining a provisioning scheme for LR, a broker can price its service for the provisioning task as

$$C = T \cdot (R_u \cdot c_R + S_u \cdot c_S) \cdot (1+\delta) = \zeta \cdot (1+\delta), \quad (1)$$

where R_u and S_u are the numbers of optical-to-electrical-to-optical (O/E/O) regenerators and FS's that need to be allocated with the provisioning scheme, c_R and c_S are the unit costs for regenerator and FS utilizations, respectively, and δ ($\delta_{max} \geq \delta \geq \delta_{min}$) is the profit ratio with which the broker adjusts its pricing strategy. Here, we assume that a broker will not provision LR for free (*i.e.*, $\delta = 0$), and it has to secure a minimum profit ratio of δ_{min} in each bid. Basically, if a broker loses a bid, its profit is 0, which is apparently better than provisioning LR for free. Since game theory is based on the principle that all the players are intelligent rational decision makers [15], our assumption above is reasonable.

We denote the base cost of *Broker* k due to regenerator and spectrum utilization as ζ_k. Then, with the prices from all the subscribed brokers as $\mathcal{C} = \{C_k, \forall k\}$, we can obtain the expectation of the profit of *Broker* k as

$$\mathcal{U}_k(\mathcal{C}) = \begin{cases} 0, & C_k > \min(\mathcal{C}), \\ \frac{\zeta_k \cdot \delta_k}{\hat{K}}, & \text{otherwise}, \end{cases} \quad (2)$$

where $\hat{K}$ is the number of the brokers whose bidding prices are the minimum. Basically, in the situation that more than one brokers offer the minimum price, the DM in the source domain randomly selects one of them as the winner.

Apparently, the long-term operation of the multi-domain SD-EON forms repeated games, and each broker can observe all the historical actions of its competitors, *i.e.*, their bidding prices. Meanwhile, the broker is rational and thus should try to maximize its profits in the long run through the repeat games. Hence, the optimization objectives of the brokers are the same:

$$\text{Maximize} \quad \mathcal{U}_k(\mathcal{C}_m), \quad \forall k, m, \quad (3)$$

where $\mathcal{C}_m$ is the set of the brokers' prices in the m-th game.

D. Nash Equilibrium

To figure out the brokers' pricing strategies, we need to determine their best responses to each other's strategies, *i.e.*, finding the "mutual best responses" for the brokers, which can be done by leveraging the concept of Nash equilibrium [15]. We first consider a simplified version of the problem, where for each LR, all the brokers receive the identical ID-VTs from the DMs and use the same RMSA algorithm to calculate the inter-domain provisioning scheme. Hence, the intra-domain provisioning schemes from the brokers should be the same and their base costs (*i.e.*, $\{\zeta_k,\ k\}$) are also the same. Then, the problem is transformed into a classic Bertrand game [27] whose Nash equilibrium can be analyzed as follows.

It is known that the Nash equilibrium of a game is the strategy profile in which no broker can increase its profit by changing the strategy unilaterally [15], which can be obtained by checking the best response function of each broker as

$$\psi_k(\mathcal{C}_{-k}) = \arg\max_{C_k} \{\mathcal{U}_k(\mathcal{C})\}, \quad \forall k, \quad (4)$$

where $\mathcal{C}_{-k}$ is the set of the prices from all the subscribed brokers except for *Broker* k, *i.e.*, $\mathcal{C}_{-k} = \mathcal{C} \setminus \{C_k\}$. Basically, the best response function provides *Broker* k the optimal price to bid for the provisioning task, when the prices from all its competitors are known. Hence, based on the discussion in the previous subsection, we can easily obtain

$$\psi_k(\mathcal{C}_{-k}) = \max\{\min(\mathcal{C}_{-k}) - \theta, \zeta_k \cdot (1+\delta_{min})\}, \forall k, \quad (5)$$

where $\theta > 0$ is a very small constant.

Let $\mathcal{C}^* = \{C_k^*, \forall k\}$ denote the Nash equilibrium of the game. Then, by definition, we have

$$C_k^* = \psi_k(\mathcal{C}_{-k}^*), \quad \forall k. \quad (6)$$

In other words, the Nash equilibrium $\mathcal{C}^*$ is the intersection of the best response functions $\psi_k(\cdot)$ of all the subscribed brokers.

Lemma 1. *$\mathcal{C}^* = \{\zeta_k \cdot (1+\delta_{min}),\ \forall k\}$ is the only Nash equilibrium in the simplified game of broker competition.*

Proof: First of all, as we know that the base costs of all the brokers are the same, we define $\zeta = \zeta_k,\ \forall k$. Then, with Eq. (5), it is easy to verify that $\zeta \cdot (1+\delta_{min})$ is a feasible solution of all the best response functions, which means that $\mathcal{C}^* = \{\zeta \cdot (1+\delta_{min}),\ \forall k\}$ is a Nash equilibrium in the simplified game of broker competition. Next, we prove the uniqueness of the Nash equilibrium by contradiction. We assume that there exists another Nash equilibrium $\widetilde{\mathcal{C}}^*$. This actually means that at least one broker (*e.g.*, *Broker* k) has $\widetilde{C}_k^* = \min\left(\widetilde{\mathcal{C}}_{-k}^*\right) - \theta > \zeta \cdot (1+\delta_{min})$, which leads to

$$\zeta \cdot (1+\delta_{min}) < \widetilde{C}_k^* < \min\left(\widetilde{\mathcal{C}}_{-k}^*\right). \quad (7)$$

If we put the inequality in Eq. (7) into Eq. (5), we can get $\widetilde{C}_h^* = \widetilde{C}_k^* - \theta < \widetilde{C}_k^*$ for each *Broker* h ($h \neq k$). This, however, is contradictory with the inequality in Eq. (7), *i.e.*, $\widetilde{C}_k^* < \min\left(\widetilde{\mathcal{C}}_{-k}^*\right)$. Finally, we prove that $\{\zeta \cdot (1+\delta_{min}), \forall k\}$ is the only Nash equilibrium in the game. ■

More specifically, *Lemma* 1 actually means that in the simplified game of broker competition, the optimal pricing strategy for each broker is to bid for the provisioning task with the lowest possible price (*i.e.*, $\zeta \cdot (1+\delta_{min})$). Under such a situation, each broker is expected to get a profit of $\frac{\zeta \cdot \delta_{min}}{K}$, where K is the number of all the subscribed brokers. Apparently, this strategy will lead to a prisoners' dilemma-like situation [15], and is Pareto inefficient for the brokers.

In practice, the problem of broker competition that we are trying to address is more sophisticated and the differences are mainly two-fold. Firstly, we consider a more practical scenario in which different brokers can receive different ID-VTs for the same domain due to the various SLAs between them and the DM. Therefore, the base costs from the brokers (*i.e.*, $\{\zeta_k,\ k\}$) can be different and unknown to each other, and the brokers can only compete with incomplete information on their competitors. This makes it difficult for the brokers to analyze the Nash equilibrium exactly. Secondly, as multiple inter-domain lightpath requests need to be served on-the-fly in dynamic network provisioning, we need to address a sequence of repeated games instead of a single one.

With these considerations, we design an effective bidding strategy based on the kernel density estimation scheme [16], which enables the brokers to predict their competitors' behaviors and then price their services in the optimal way. The strategy will be discussed in the next section, and in Section VI, we will show that it makes the brokers more profitable than the Nash equilibrium defined in *Lemma* 1.

IV. Broker Bidding Strategy

In the repeated games on bidding for inter-domain provisioning tasks, a broker should analyze all its competitors' behaviors based on the information from historical games. We define C_k^m as the price from *Broker* k in the m-th game, and $\mathcal{R}_k^m$ as the corresponding game result, *i.e.*, $\mathcal{R}_k^m = 1$ if *Broker* k wins the m-th game, and $\mathcal{R}_k^m = 0$ otherwise. We assume that there have been M games since the system starts, and each broker analyzes all its competitors' behaviors based on the information from Q historical games, *i.e.*, the size of the prediction window is Q. Hence, we obtain an integer set $\mathcal{I}_k = \left\{m : m \in [M-Q+1, M],\ \mathcal{R}_k^{m-1} = \mathcal{R}_k^M\right\}$ to represent the indices of all the historical games that are used in the prediction. This means that in order to improve the preciseness of the prediction, we only consider the historical games whose immediately previous games provide the same result to *Broker* k as the most recent one (*i.e.*, the M-th game).

Then, in the current game (*i.e.*, the $(M+1)$-th game), a broker k_0 can estimate the probability density function (PDF) of the price from another broker k ($k \neq k_0$) by employing the Gaussian kernel density estimation (KDE) scheme developed in [16], as

$$\hat{p}_k(x) = \sum_{m\in\mathcal{I}_k} \frac{\omega_m}{\sqrt{2\pi}\cdot\sigma_k} \exp\left\{\frac{\left(x - \frac{\zeta_{k_0}^{M+1}}{\zeta_{k_0}^m}\cdot C_k^m\right)^2}{-2\sigma_k^2}\right\}, \quad (8)$$

where σ_k is the kernel width, ω_m is the prediction weight such that $\sum\limits_{m\in\mathcal{I}_k} \omega_m = 1$, and $\zeta_{k_0}^m$ is the base cost from *Broker* k_0 in the m-th game. Basically, the estimated PDF is the weighted summation of a series of Gaussian functions that are centered at the corresponding historical prices. Since the base costs from the brokers can vary due to the difference in provisioning schemes and due to the fact that *Broker* k_0 is unaware of the base cost from *Broker* k in the current game, we normalize the price from *Broker* k in each previous game with the ratio between the base costs of that game and the current one from *Broker* k_0, *i.e.*, using the term $\frac{\zeta_{k_0}^{M+1}}{\zeta_{k_0}^m}\cdot C_k^m$ in Eq. (8). We define

$$\widetilde{C}_k^m = \frac{\zeta_{k_0}^{M+1}}{\zeta_{k_0}^m}\cdot C_k^m. \quad (9)$$

Fig. 2 shows an illustrative example on the Gaussian kernel density estimation. For the five historical games that are used in the prediction for *Broker* k, we have historical prices $\{\widetilde{C}_k^m\} = \{4.5, 5.0, 5.5, 8.0, 12.0\}$, $\sigma_k = 1$, and $\omega_m = 0.2$. Then, the PDF is estimated with five Gaussian functions.

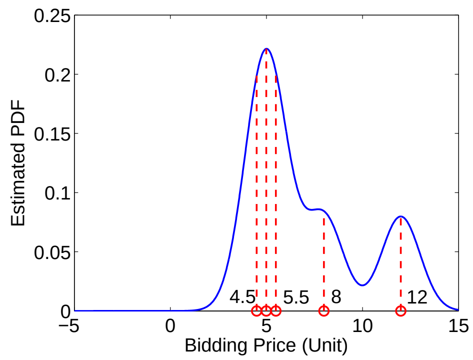


Fig. 2. An example for Gaussian kernel density estimation.

It is known that how to determine the kernel width σ_k is essential for obtaining a good PDF approximation with the Gaussian kernel density estimation [16]. Let $p_k(x)$ be the real PDF of the price from *Broker* k, and with the cross-validation method in [28], we can get the optimal value of σ_k by minimizing the integrated squared error (ISE) below

$$\begin{aligned} ISE(\sigma_k) &= \int [\hat{p}_k(x) - p_k(x)]^2 \mathrm{d}x \\ &= \int \hat{p}_k^2(x)\mathrm{d}x - 2\int \hat{p}_k(x)\cdot p_k(x)\mathrm{d}x + \int p_k^2(x)\mathrm{d}x. \end{aligned} \quad (10)$$

As $\int p_k^2(x)\mathrm{d}x$ is independent of σ_k and $\int \hat{p}_k(x)\cdot p_k(x)\mathrm{d}x$ is the expectation of $\hat{p}_k(x)$, Eq. (10) can be rewritten as

$$f(\sigma_k) = ISE(\sigma_k) - \int p_k^2(x)\mathrm{d}x = \int \hat{p}_k^2(x)\mathrm{d}x - 2E\{\hat{p}_k(x)\}. \quad (11)$$

Here, $E\{\hat{p}_k(x)\}$ can be estimated by

$$E\{\hat{p}_k(x)\} \approx \frac{1}{|\mathcal{I}_k|}\sum_{m\in\mathcal{I}_k} \hat{p}_{k,-m}(\widetilde{C}_k^m), \quad (12)$$

where the function $\hat{p}_{k,-m}(\cdot)$ has the expression of

$$\hat{p}_{k,-m}(x) = \frac{1}{1-\omega_m}\sum_{n\in\mathcal{I}_k, n\neq m} \frac{\omega_n}{\sqrt{2\pi}\cdot\sigma_k}\exp\left\{\frac{\left(x-\widetilde{C}_k^n\right)^2}{-2\sigma_k^2}\right\}, \quad (13)$$

and it is the leave-one-out estimator [28]. Meanwhile, $\int \hat{p}_k^2(x)\mathrm{d}x$ can be calculated as

$$\int \hat{p}_k^2(x)\mathrm{d}x = \sum_{m\in\mathcal{I}_k}\sum_{n\in\mathcal{I}_k} \frac{\omega_m\cdot\omega_n}{\sqrt{4\pi}\cdot\sigma_k}\exp\left\{\frac{\left(\widetilde{C}_k^m-\widetilde{C}_k^n\right)^2}{-4\sigma_k^2}\right\}. \quad (14)$$

By combining Eqs. (11)-(14), we get $f(\sigma_k)$ as

$$\begin{aligned} f(\sigma_k) = &\sum_{m\in\mathcal{I}_k}\sum_{n\in\mathcal{I}_k} \frac{\omega_m\cdot\omega_n}{\sqrt{4\pi}\cdot\sigma_k}\exp\left\{\frac{\left(\widetilde{C}_k^m-\widetilde{C}_k^n\right)^2}{-4\sigma_k^2}\right\} - \\ &\sum_{m\in\mathcal{I}_k}\sum_{n\in\mathcal{I}_k, n\neq m} \frac{2\omega_n}{\sqrt{2\pi}\sigma_k(1-\omega_m)|\mathcal{I}_k|}\exp\left\{\frac{\left(\widetilde{C}_k^m-\widetilde{C}_k^n\right)^2}{-2\sigma_k^2}\right\}. \end{aligned} \quad (15)$$

Hence, we can determine the optimal value of σ_k as

$$\sigma_k^* = \arg\min \{f(\sigma_k)\}, \quad \forall k. \tag{16}$$

With Eqs. (8) and (15)-(16), we can estimate the PDF of the price from *Broker* k precisely. Then, after having obtained the PDFs of the prices from all of its competitors, *Broker* k_0 can determine the optimal bidding price for the current game (*i.e.*, $(C_{k_0}^{M+1})^*$) by solving the following optimization problem

$$(C_{k_0}^{M+1})^* = \arg\max_{C} \left\{ \left(C - \zeta_{k_0}^{M+1}\right) \prod_{k \neq k_0} \left(\int_C^{\infty} \hat{p}_k(x) \mathrm{d}x \right) \right\}. \tag{17}$$

Basically, *Broker* k_0 can win the game when and only when all the other subscribed brokers offer higher prices than it. Hence, Eq. (17) tries to maximize the expected profit of *Broker* k_0. In order to solve Eq. (17) for $(C_{k_0}^{M+1})^*$, we can take the logarithm of the term inside $\arg\max_{C} \{\cdot\}$ and obtain

$$\begin{aligned} z(C) &= \log \left\{ \left(C - \zeta_{k_0}^{M+1}\right) \prod_{k \neq k_0} \left(\int_C^{\infty} \hat{p}_k(x) \mathrm{d}x \right) \right\} \\ &= \log(C - \zeta_{k_0}^{M+1}) + \sum_{k \neq k_0} \log \int_C^{\infty} \hat{p}_k(x) \mathrm{d}x. \end{aligned} \tag{18}$$

Finally, the optimal bidding price $(C_{k_0}^{M+1})^*$ can be determined by checking the zero points of $\frac{\mathrm{d}z(C)}{\mathrm{d}C}$, as

$$\begin{aligned} \frac{\mathrm{d}z(C)}{\mathrm{d}C} &= \frac{1}{C - \zeta_{k_0}^{M+1}} + \sum_{k \neq k_0} \frac{-\hat{p}_k(C)}{\int_C^{\infty} \hat{p}_k(x) \mathrm{d}x} \\ &= \frac{1}{C - \zeta_{k_0}^{M+1}} + \sum_{k \neq k_0} \frac{-\hat{p}_k(C)}{1 - \sum\limits_{m \in \mathcal{I}_k} \omega_m \cdot \Phi\left(\frac{C - \tilde{C}_k^m}{\sigma_k}\right)}, \end{aligned} \tag{19}$$

where the function $\Phi(\cdot)$ has the expression of

$$\Phi(C) = \int_{-\infty}^{C} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{x^2}{2}\right) \mathrm{d}x. \tag{20}$$

V. NC&M System Implementation

We implement the proposed multi-broker based incentive-driven service provisioning framework in an OpenFlow-based NC&M system for multi-domain SD-EONs. Basically, the system utilizes the network architecture in Fig. 1, where the DMs are realized with OpenFlow controllers (OF-C) based on the POX platform [29] and the brokers are implemented with our own software modules. Meanwhile, since this work concentrates on the NC&M operations in multi-broker based multi-domain SD-EONs, the optical switches are software-emulated, each of which is programmed based on Open-vSwitch [29] and runs on an independent Linux server.

Fig. 3(a) illustrates the operation principle of the multi-domain SD-EON system, while each step of the procedure is explained in details in Table I. Here, the OF-Cs communicates with optical switches using the extended OpenFlow protocol defined in [10], and we reuse the *Packet_In* message to carry the information of a lightpath request. In order to facilitate cost-effective inter-domain service provisioning, each OF-C provides ID-VTs to its subscribed brokers. Specifically, for

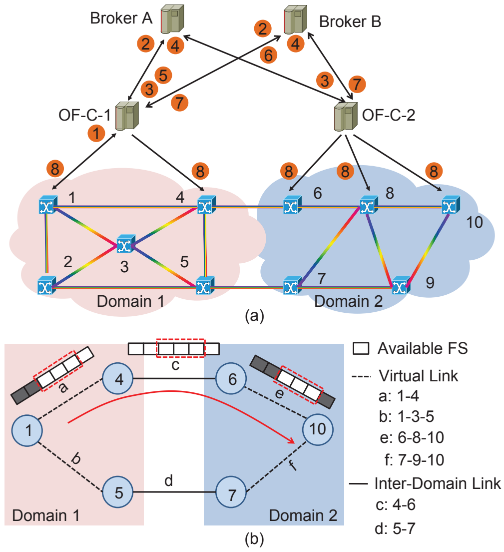


Fig. 3. Operation principle of multi-broker based multi-domain SD-EON system, (a) working procedure and (b) ID-VT abstraction.

an inter-domain lightpath request $LR(s, d, B, T)$, an ID-VT includes the intra-domain information of the spectrum utilizations, hop counts, and physical lengths of the virtual links (VLs), which are abstracted from the path segments that are from s to egress nodes in the source domain, between ingress nodes and egress nodes in intermediate domains, and from ingress nodes to d in the destination domain. For example, in Fig. 3(b), *VL* a and e correspond to *Path Segments* 1-4 and 6-8-10 in Fig. 3(a), respectively. Then, each broker constructs a virtual topology G' with the acquired information, and uses G' to calculate a RMSA solution for provisioning LR.

Here, we apply the K-shortest path routing and impairment-aware RMSA scheme, and each broker decides the modulation-formats to be used on the whole or partial candidate paths of LR based on the quality-of-transmission (QoT) [30]. More specifically, we assume each modulation-format is related to a maximum transparent transmission reach and the brokers will select the modulation-format with the highest spectral efficiency under such constraint. Once the modulation-format is determined, the number of required FS's n can be computed as $n = \left\lceil \frac{B}{m \cdot C_{grid}^{BPSK}} \right\rceil$, where C_{grid}^{BPSK} is the transmission capacity of an FS when it uses BPSK as the modulation-format, and $m = 1, 2, 3$ and 4 represents the modulation-levels of BPSK, QPSK, 8-QAM and 16-QAM, respectively. Meanwhile, we assume that O/E/O regenerators can be used on the border nodes between domains, when a spectrum conversion has to be performed or a lightpath does not even satisfy the QoT requirement of the lowest modulation-level (*i.e.*, BPSK). Finally, each broker performs spectrum assignment with the specified scheme on the candidate paths and select the one with the lowest base cost as the RMSA solution. To realize the procedure in Table I, we leverage the inter-domain protocol (IDP) that we designed in [11, 18] to facilitate the communications between the brokers and OF-Cs, and Fig. 4 shows the formats of the messages used in the IDP. Basically, we incorporate some

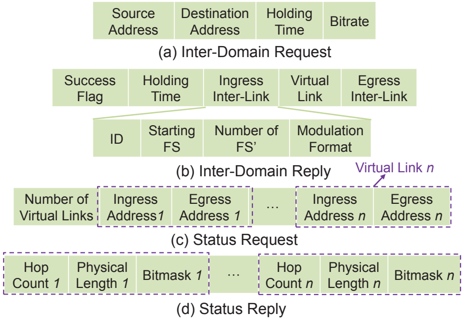


Fig. 4. Messages designed for the inter-domain protocol (IDP).

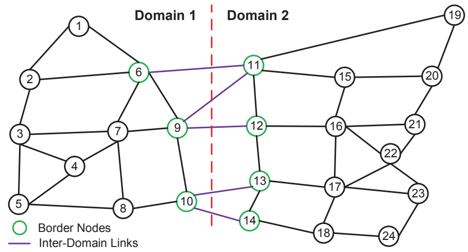


Fig. 5. Network topology of experimental testbed.

minor extensions to the IDP and make it adapt to the multi-broker scenario. Meanwhile, we hope to point out that the communications between the brokers and OF-Cs can also be realized by extending the existing path computation element communication protocol (PCEP) discussed in [31, 32], as it also considers the economic aspects of multi-domain SD-EONs. In our future work, we will study how to treat our IDP design as a new extension in PCEP.

TABLE I
OPERATION PRINCIPLE OF MULTI-BROKER BASED MULTI-DOMAIN SD-EON SYSTEM

Step 1: An inter-domain lightpath request $LR(s=1,d=10,B,T)$ arrives at the OF-C of its source domain (*i.e.*, OF-C-1) through a *Packet_In* message.
Step 2: OF-C-1 forwards LR's information to all its subscribed brokers with *Inter_Domain_Request* messages.
Steps 3 and **4**: Upon receiving the information on LR, each broker interacts with OF-Cs using *Status_Request* and *Status_Reply* messages for getting ID-VTs.
Step 5: Each broker performs RMSA for LR, calculates the price for its provisioning service with Eqs. (8)-(20)[2], and returns the price to the source domain's OF-C (*i.e.*, OF-C-1) using a *Provision_Request* message.
Step 6: After obtaining the prices from all the brokers, OF-C-1 selects the broker that offers the lowest price as the winner and commits its provisioning task with a *Provision_Reply* message.
Step 7: The winning broker distributes the inter-domain provisioning scheme that it calculated before to each related OF-C using an *Inter_Domain_Reply* message.
Step 8: Each OF-C sets up the lightpath segment in its domain accordingly, by sending a *Flow_Mod* message to each related optical switch, and finally, LR is provisioned successfully.

VI. EXPERIMENTAL RESULTS

We conduct inter-domain service provisioning experiments in the multi-broker based multi-domain SD-EON testbed, which includes two domains and each of the DMs subscribes to two brokers. Fig. 5 shows the network topology used in the experimental testbed. We assume that the network operates in the C-band and hence each fiber can accommodate 358 FS's, each of which has a bandwidth of 12.5 GHz, *i.e.*, $C_{grid}^{BPSK}=12.5$ Gb/s. The maximum number of O/E/O regenerators on each border node is set as 50. The lightpath requests are generated dynamically according to the Poisson traffic model, with their source and destination nodes randomly selected. This means that a lightpath request can use any node in the topology as its source and destination, while its spectrum assignment can only be changed on intermediate border nodes with O/E/O regenerations. We apply this constraint to ensure that the additional operational cost and energy consumption due to O/E/O regenerations can be controlled well. The bandwidth requirements follow a uniform distribution within $[25,500]$ Gb/s. The unit costs for using an FS and a regenerator per provision period are set as $c_S=1$ and $c_R=5$ units, respectively. Note that, since this work focuses on inter-domain service provisioning, we only collect experimental results related to inter-domain lightpath requests.

Meanwhile, we assume that based on their SLAs, the two brokers gets different ID-VTs from each DM. Specifically, for *Broker* 1, each DM abstracts the ID-VTs by calculating the path segments (*i.e.*, VLs) with shortest-path routing, and thus we refer *Broker* 1 as Broker-SP in this section. On the other hand, for *Broker* 2, the DMs calculate VLs as the path segments that have the maximum available FS's, and hence *Broker* 2 is named as Broker-LB. Note that, after obtaining the ID-VTs from the DMs, each broker tries to provision an inter-domain lightpath request with three RMSA algorithms, *i.e.*, K-shortest path and first-fit (KSP-FF) [7], K-shortest path and load-balancing (KSP-LB) [33], and fragmentation-aware RMSA (FA) [34], and uses the provisioning scheme that has the lowest base cost in the bidding for the provisioning task.

A. One-Time Provisioning with Multiple Brokers

We first perform an experiment on one-time service provisioning with multiple brokers to verify that the proposed system can operate correctly. Fig. 6 shows the message list captured on an OF-C for setting up an inter-domain lightpath from *Node* 2 to *Node* 20. It can be seen that the system works exactly according to our design, *i.e.*, *Brokers* 1 and 2 compete for the provisioning task and *Broker* 1 finally wins the game. The whole process only takes around 42 msec. Fig. 7 shows the wireshark captures of the *Status_Reply*

[2]Note that, according to the rational assumption in game theory, the brokers should apply the bidding strategy to maximize their profits. Hence, we make the brokers use our proposed bidding strategy as it is the most effective one we have found so far. By doing so, we respect the rationality assumption in game theory and also realize a relatively fair comparison.

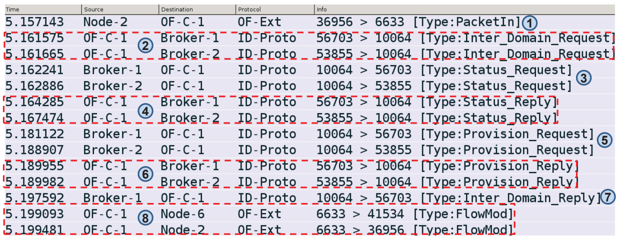


Fig. 6. List of messages used for setting up an inter-domain lightpath.

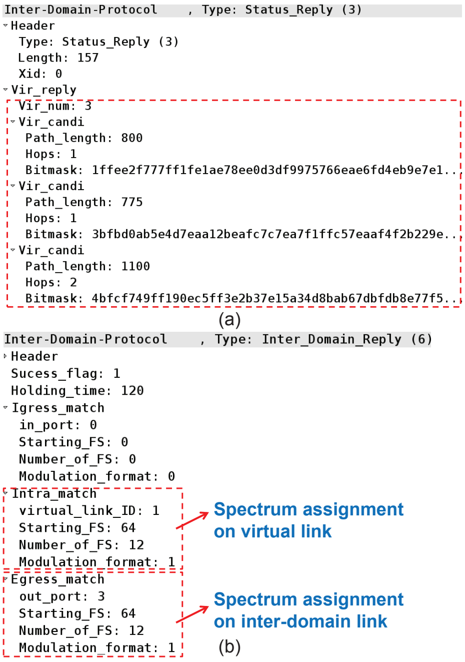


Fig. 7. Wireshark captures of (a) *Status_Reply* and (b) *Inter_Domain_Reply* messages.

(*i.e.*, from OF-C-1 to *Broker* 1) and *Inter_Domain_Reply* (*i.e.*, from *Broker* 1 to OF-C-1) messages used in the experiment. We observe that OF-C-1 abstracts an ID-VT to report the information of three VLs (*i.e.*, 2-6, 2-6-9 and 2-3-5-8-10), such as their path lengths, hop counts and spectrum utilizations, in the *Status_Reply* message to *Broker* 1. While after *Broker* 1 winning the game, it instructs OF-C-1 to use the first VL to set up the path segment within its domain with the assigned spectra as the FS-block $[64, 75]$ and the selected modulation-format as BPSK. Meanwhile, *Broker* 1 provides the modulation and spectrum assignments on the inter-domain link to OF-C-1, which is the same as that on the preceding intra-domain segment. Hence, the inter-domain lightpath is set up transparently from within *Domain* 1 to *Domain* 2, and there is no need to allocate an O/E/O regenerator on the corresponding border node (*i.e.*, *Node* 6).

B. Dynamic Service Provisioning with Repeated Games

We conduct experiments on dynamic service provisioning with repeated games first to verify the effectiveness of the proposed multi-broker based multi-domain SD-EON architecture when compared with the single-broker based scheme in

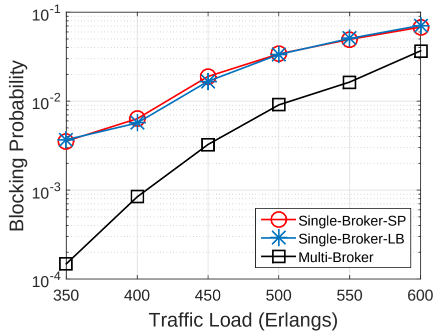


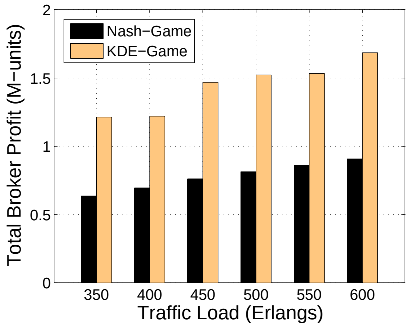
Fig. 8. Request blocking probabilities from single- and multi-broker based scenarios.

[19]. Here, the multi-broker based scheme uses our designed bidding strategy. We set $\delta_{min} = 0.1$, $\delta_{max} = 1$, the size of the prediction window as $Q = 300$, and the prediction weights as $\omega_m = \frac{2m}{Q\cdot(1+Q)}$, *i.e.*, the weights of the historical prices increase linearly with m (the index of a historical game).

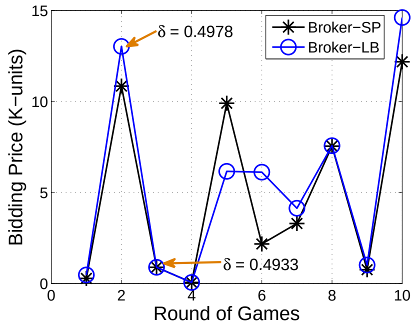
Fig. 8 shows the results on request blocking probability. It is interesting to notice that the multi-broker based scheme achieves lower blocking probability than the single-broker based schemes, which can be explained as follows. Basically, in the multi-broker based scheme, an "optimal" provisioning scheme is determined for each request through the competition of the brokers, *i.e.*, the source DMs have the option of choosing the provisioning schemes with the lowest prices. Hence, the overall network resource utilization is arranged with high efficiency. However, this is not possible in the single-broker based scheme. Therefore, the multi-broker based scheme can outperform the single-broker based schemes in terms of blocking probability.

We then compare the performance of the proposed broker bidding strategy to that implied by the Nash equilibrium obtained in Section III-D. Here, we name the scenario in which both brokers operate according to the Nash equilibrium as Nash-Game, where the brokers always submit the lowest possible price to bid for the provisioning tasks. Our proposed bidding strategy is referred as KDE-Game. Fig. 9(a) shows the results on total broker profits versus traffic loads, and it can be seen that KDE-Game always achieves much higher profit than Nash-Game. This is because with our proposed bidding strategy, the brokers can predict the behaviors of their competitors and then adjust their profit ratios intelligently for maximizing their profits. This can be verified with the results in Fig. 9(b), which samples the evolution of the bidding prices from the brokers in KDE-Game. We can see that Broker-LB decreases its profit ratio δ from 0.4978 to 0.4933 when it has lost the second game, and then it wins the third game.

To study KDE-Game further, we also plot the profits of Broker-SP and Broker-LB, which obtain different intra-domain information from the OF-Cs, in Fig. 10. It can be seen that Broker-SP outperforms Broker-LB all the time, for the reason that it calculates provisioning schemes with lower base costs by using the shorter VLs from OF-Cs. Therefore, it holds advantage in the game. We also observe that the advantage



(a) Total profit of brokers (Nash-Game *versus* KDE-Game).



(b) Evolution of bidding prices from brokers.

Fig. 9. Experimental results from long-term repeated games.

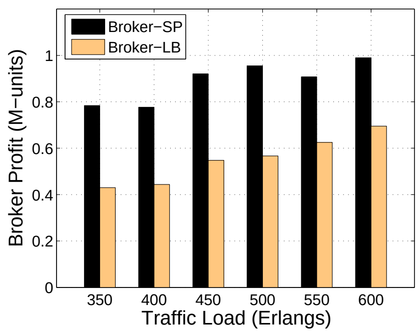


Fig. 10. Total profits of KDE-Game brokers (Broker-SP *versus* Broker-LB).

from Broker-SP over Broker-LB gets smaller when the traffic load increases. This is because by using the VLs that carry more available FS's, Broker-LB can potentially provision more requests than Broker-SP in a more congested network.

Finally, we conduct experiments in which the brokers can use different values of Q (*i.e.*, the size of the prediction window), and investigate the impact of Q on the brokers' profits. The results are summarized in Table II. Here, we only show the results with the traffic load as 450 Erlangs, but have verified that the results under different traffic loads exhibit the similar trend. It is interesting to notice that the profit of each broker tends to decrease with the increase of Q. This is because with a larger Q, a broker can acquire a more accurate estimation on its competitor's behavior and its competitor has no choice but to reduce the bidding prices to ensure certain profit gain, which would squeeze the profit ratios achieved by both brokers. Basically, as both brokers leverage the KDE-based bidding strategy, the decisions made by them impact the profits of each other mutually, which means that the broker in turn would have to reduce its profit ratios to maintain competitiveness in the game. However, these results would not necessarily suggest that using a smaller Q would make a broker more profitable in any case. This is because in a practical scenario, some brokers may apply other bidding strategies or even change their strategies dynamically. Hence, letting a broker use a relatively large Q (*e.g.*, $Q = 300$) can make sure that it can possess sufficient cognition on its competitors' behaviors. Meanwhile, how to decide the value of Q in different network scenarios is still an open question to us, and we will study it in our future work.

VII. Conclusion

This paper studied the incentive-driven service provisioning in multi-broker based multi-domain SD-EONs. We first presented the theoretical model of the network operations to describe the noncooperative game in which the brokers compete for inter-domain provisioning tasks with only incomplete information on their competitors. Then, we analyzed the Nash equilibrium in a simplified version of the game, and showed that to maximize the brokers' profits in long-term repeated games, an effective bidding strategy is needed for the brokers to predict their competitors' behaviors and price their services in the optimal way. We designed the bidding strategy by leveraging the kernel density estimation scheme. Finally, to demonstrate the effectiveness of our bidding strategy, we implemented it in an OpenFlow-based multi-domain SD-EON control plane testbed. Our experimental results verified that the system performs well and the brokers can obtain higher profits with the proposed bidding strategy in repeated games.

Acknowledgments

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TABLE II

TOTAL PROFITS OF KDE-GAME BROKERS WITH DIFFERENT VALUES OF Q (450 ERLANGS).

Broker Profits (M-units) Q_2 / Q_1	1	50	100	200	300	500
1	2.523, 1.898	2.097, 1.482	1.802, 1.361	1.451, 1.127	1.302, 1.010	1.232, 0.944
50	1.627, 1.191	1.704, 0.999	1.632, 0.937	1.740, 0.949	1.498, 0.824	1.262, 0.690
100	1.531, 1.087	1.475, 0.844	1.376, 0.804	1.471, 0.835	1.364, 0.738	1.293, 0.714
200	1.107, 0.790	1.076, 0.640	1.418, 0.804	1.306, 0.761	1.201, 0.710	1.155, 0.654
300	1.003, 0.698	1.239, 0.766	1.121, 0.695	0.968, 0.590	1.236, 0.715	1.114, 0.643
500	1.052, 0.816	1.033, 0.668	1.028, 0.659	0.953, 0.574	1.077, 0.688	1.133, 0.698

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