Near Optimal and Dynamic Mechanisms Towards a Stable NFV Market in Multi-Tier Cloud Networks

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***Abstract*—With the fast development of next-generation networking techniques, a Network Function Virtualization (NFV) market is emerging as a major market that allows network service providers to trade various network services among consumers. Therefore, efficient mechanisms that guarantee stable and efficient operations of the NFV market are urgently needed. One fundamental problem in the NFV market is how to maximize the social welfare of all players, so they have incentives to participate in activities of the market. In this paper, we first formulate the social welfare maximization problem, with an aim to maximize the total revenue of all players in the NFV market. For the social welfare maximization problem, we design an efficient incentive-compatible mechanism and analyze the existence of a Nash equilibrium of the mechanism. We also consider an online social welfare maximization problem without the knowledge of future request arrivals. We devise an online learning algorithm based on Multi-Armed Bandits (MAB) to allow both customers and network service providers to make decisions with uncertainty of customers' strategy. We evaluate the performance of the proposed mechanisms by both simulations and test-bed implementations, and the results show that the proposed mechanisms obtain at most 23% higher social welfare than existing studies.**

***Index Terms*—Mobile edge clouds, network function virtualization, near optimal incentive-compatible mechanisms, price of anarchy, online learning.**

I. Introduction

With the fast development of 5G technology, a market that regulates the production and consumption of 5G network services is emerging. For example, the global 5G network services market is expected to grow from USD 53.93 billion in 2020 to USD 123.27 billion by 2025, at a Compound Annual Growth Rate (CAGR) of 18.0% during the forecast period [1]. The ETSI Industry Specification Group on Network Function Virtualization (NFV) is developing a set of specifications and reports to enable an open NFV market [25]. In such a market, various 5G service providers can build services consisting of sequences of Virtualized Network Functions (VNF) and offer customers on demand [4], [42]. Customers can browse a list of available service chains offered by each network service provider to implement their services. The interactions between network service providers and customers are important to guarantee the success of a NFV market. We thus investigate the problem how to maximize the social welfare of the markets such that all players can maximize their revenues. To this end, network service providers need to carefully determine the placement locations and prices of VNF instances, given that each player is selfish and aims to maximize his/her own revenue. In this paper, we consider the social welfare maximization problem in a NFV market in a mobile edge cloud, by designing stable and efficient mechanisms, such that the social welfare of the market is maximized.

Designing efficient mechanisms for stable and efficient operations of a NFV market is challenging. First, VNF placements need considering both the resource requirement of VNFs and the demands of traffic routing. Second, there exist various selfish players in the NFV market, such as network service providers and customers. It is challenging to design an incentive-compatible and stable mechanism with a Nash equilibrium (NE), so that both network service providers and customers have incentives to participate in the NFV market to obtain revenues. Besides, the social welfare achieved through the NE needs to be guaranteed to ensure that such a solution is not far from the optimal one. Third, considering that existing customers may leave and new customers may enter the NFV market, how to design an "online mechanism" that allows network service providers to quickly determine the optimal locations for their VNFs to respond to dynamic requests. Fourth, customers' strategies are usually not known by other customers and the network service provider, how to design an "online mechanism" that allows network service providers to determine the optimal locations for their VNFs without complete information of customers is the fourth challenge.

Although there are extensive studies on NFV in both software defined networks, mobile edge networks, and conventional cloud networks [19], [27], [28], [35], [36]. There are only several studies on mechanism design for NFV markets [4],

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[42], by proposing a double-auction approach [4] or an online stochastic buy-sell mechanism [42]. These proposals basically require a central or multiple collaborating brokers to implement the mechanisms, and may suffer the scalability issues.

To the best of our knowledge, we are the first to investigate the online social welfare maximization problem in a NFV market under a mobile edge network. The main contributions of this paper are as follows.

- We formulate the social welfare maximization problem in a NFV market with multiple network service providers leasing virtual machine (VM) resources to implement VNF services, as well as customers with NFV-enabled requests. Then we formulate the online social welfare maximization problem with stochastic arriving requests.
- We develop an effective mechanism for the social welfare maximization problem, and show that the mechanism is incentive-compatible and exists at least one NE for it.
- We analyze the quality of the NE by showing the Price of Anarchy (PoA) of the NE, which quantifies the worse case gap between the social welfare of the NE and the optimal solution with non-selfish players.
- For the online social welfare maximization problem with stochastic arriving requests and without complete information of customers, we design an online algorithm based on the Multi-Armed Bandit (MAB) method that allows network service providers to determine the optimal locations for their VNFs with a bounded regret.
- We evaluate the performance of the proposed algorithms by extensive simulations and test-bed implementations. The results show that the proposed algorithm obtains at most 23% higher social welfare than existing studies.

The remainder of the paper is arranged as follows. Section II summarizes the state-of-the-art of related studies. Section III introduces the system model and defines the problems. Section IV provides an incentive-compatible facility location game for the social welfare maximization problem. Section V devises an online learning algorithm for the online social welfare maximization problem with uncertain customer strategy. Section VI provides some experimental results, and Section VII concludes the paper.

II. Related work

Network function virtualization has attracted much attention in the past few years [3], [5], [6], [8], [10], [11], [14], [15], [18], [19], [21], [23], [24], [27], [30], [31], [32], [33], [38], [39], [43], [44], [45]. Although there are many studies on the provisioning and allocation of VMs in cloud networks [7], [9], [12], [13], [22], [34], [37], [40], they have a fundamental difference from the VNF service provisioning in a NFV market. That is, serving service chain requests in a NFV market require not only the placement of VNFs (run in VMs) but also traffic routing of customer requests from their sources to destinations. For example, Ficco *et al.* [7] proposed a meta-heuristic method for optimal allocation of cloud resources based on coral-reefs and game theory. Hassan *et al.* [13] proposed two different kinds of utility maximization cooperative games with the aim to maximize the total profit of the cloud provider. Zaman *et al.* [40] proposed two combinatorial auction-based mechanisms for VM instance allocation in clouds, which bring a higher revenue to cloud providers. Ghribi *et al.* [9] introduced energy-aware VM allocation and migration algorithms in data centers. Verma *et al.* [32] proposed a multi-armed bandit based algorithm to maximize the expected total utility of the network. Jin *et al.* [15] formulated a VNF chain deployment problem as a mixed integer linear programming to minimize the total resource consumption. Yao *et al.* [38] propose an efficient online scaling algorithm, which is composed of two parts: 1) One is Fourier-Series-based forecasting approach to minimize cost by avoiding frequent changes in network topology and 2) the other is online deployment algorithm to properly deploy VNF instances.These algorithms can reduce more than 20% cost while maintaining the same system performance as other heuristic algorithms. Xu *et al.* [34] provided a comprehensive survey of managing VM performance in cloud computing, in which many similar studies on VM provisioning can be found. Although game theory can be applied to allocation and pricing of VM resources, it is seldom used in the allocation and placement of VNFs. These proposed methods thus cannot be directly applied to VNF placement in mobile edge clouds. There are several studies on mechanism design for NFV markets [4], [42], which are closely related to the study of this paper. For example, Borjigin *et al.* [4] devised a double-auction approach for resource allocation in NFV markets, with an objective to maximize the profits of a NFV broker, customers and resource suppliers. Zhang *et al.* [42] devised an online stochastic by-sell mechanism for network function chaining in a NFV market. These studies need a central or multiple collaborating brokers to implement the mechanisms, and may prohibit the scalability of the proposed mechanisms.

III. Preliminaries

A. System model

We consider a multi-tier cloud network $G = (\mathcal{CL} \cup \mathcal{DC}, E)$ consisting of a set CL of cloudlets in a mobile edge network, a set $\mathcal{DC}$ of remote data centers in the core network, and a set E of links (or VPN paths) that interconnect cloudlets and data centers. We consider the scenario that different network service providers may not have their own infrastructures, but they can lease Virtual Machines (VMs) from an infrastructure provider to implement their VNFs. We thus consider a NFV market consisting of a number of network service providers that offer services in terms of VNFs in their resource pools located in different cloudlets or data centers. We assume that each location can only accommodate a finite number of VMs to implement VNFs. Let $\mathcal{VM}_j$ be the set of available VMs in the location $L_j \in \mathcal{CL} \cup \mathcal{DC}$. $VM_{j,m}$ is the mth VM in $\mathcal{VM}_j$. Following the policies of most infrastructure providers [2], each VM has an uploading bandwidth capacity constraint $B^u_{j,m}$ and a download bandwidth capacity constraint $B^d_{j,m}$.

There are Q network service providers in the system, and sp_i denote the ith network service provider, where $1 \leq i \leq Q$. In addition, there are N consumers that request different network service chains from these Q network service providers. Let u_k be the kth customer, where $1 \leq k \leq N$. Each consumer u_k is selfish and can choose an instance of its VNF from any network service provider to reach lower costs when its performance requirement is met. Fig. 1 illustrates a multi-tier cloud network that consists of service providers offering network services to various customers who have NFV-enabled requests.

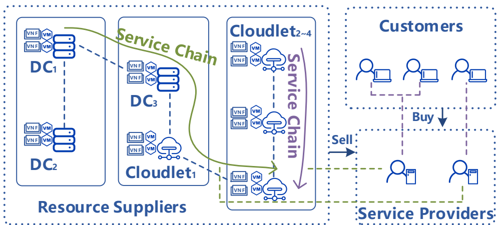


Fig. 1. A multi-tier cloud network with network service providers offering network services to customers with NFV-enabled requests.

B. NFV-enabled requests

In a NFV market, customers purchase network services to process and transfer their data. Each request requires a sequence of VNFs in a specified order, such that the performance and security of its data transfer is guaranteed. Denote by r_k a NFV-enabled request of consumer u_k. It specifies a source node s_k and a destination node t_k, and needs to transfer its traffic at a rate of ρ_k. In addition, request r_k requires to process its traffic by its specified sequence of VNFs, referred to as a *service function chain*, before reaching destination t_k. Let SC_k be the service chain of request r_k. Let f_l be lth VNF in SC_k, where $1 \leq l \leq |SC_k|$. Let $\mathcal{F}$ be the set of network functions provided by all network service providers in the multi-tier cloud network. To reduce the communication cost of transferring traffic among the VNFs of each SC_k, the network functions in SC_k are usually consolidated into a single location [3].

C. Cost and social welfare model

Service providers sell network services to customers for implementations of their NFV-enabled requests. The costs of implementing a NFV-enabled request using leased VMs include the usage costs of both computing and bandwidth resources. We assume that the cost of processing the traffic of each request r_k in a VNF at location $L_j \in \{\mathcal{CL} \cup \mathcal{DC}\}$ is proportional to the amount of traffic to be processed. Let $c^p_{k,j}$ be the cost of processing a unit data of r_k in L_j. The cost $c_{k,j}$ of placing service chain SC_k of r_k in location L_j thus is

$$c_{k,j} = c^p_{k,j} \cdot \rho_k. \tag{1}$$

Following the conventional settings of most infrastructure providers, we assume that network service providers lease a certain amount of bandwidth resource to transfer data in/out of a location $L_j \in \{\mathcal{CL} \cup \mathcal{DC}\}$. The bandwidth cost of each NFV-enabled request r_k is proportional to the amount of data it needs to transfer. Let $c^b_{k,j}$ be the cost of transmitting a unit of data traffic from s_k of request to location L_j, which can be derived by finding a shortest path from s_k to L_j. Then, the bandwidth consumption cost for request r_k in L_j is $c^b_{k,j} \cdot \rho_k$.

Network service provider sp_i sells its network services in terms of instances of VNFs to its customers at a price. Let $p_{i,k}$ be the price that network service provider sp_i asks for an instance of service chain SC_k. A customer u_k has to pay the asked price by sp_i for using its service chain to process data traffic. The payoff δ_i received by sp_i thus is

$$\delta_i = p_{i,k} - \rho_k(c^p_{k,j} + c^b_{k,j}). \tag{2}$$

Each customer u_k receives a value for a *service chain instance* of SC_k provided by network service provider sp_i, which is denoted by $\pi_{i,k}$. If it pays a price $p_{i,k}$ to use service chain SC_k, it collects a revenue of

$$\Delta_k = \pi_{i,k} - p_{i,k}. \tag{3}$$

A customer only buys an instance of its service chain from service provider sp_i if $\pi_{i,k} \geq p_{i,k}$, and it pays $p_{i,k}$. Note that network service provider sp_i does not know the exact value of $\pi_{i,k}$, and it can only observe customer's decisions to buy the implementation or not.

Since we have multiple players in the NFV market, we aim to maximize the *social welfare*, i.e., the total revenue received by all players that participate in the NFV market. Let $\Phi_{Q,N}$ be the social welfare in a NFV market with Q network service providers and N customers. $\Phi_{Q,N}$ can be calculated by

$$\Phi_{Q,N} = \sum\nolimits_{i=1}^{Q} \delta_i + \sum\nolimits_{k=1}^{N} \Delta_k. \tag{4}$$

D. Game theory and Nash equilibrium

We consider a game that has Q network service providers and N customers as players. Each network service provider sp_i provides its network services to customers by instantiating consolidated service chains in leased VMs. Each customer u_k selects an instance of its service chain SC_k from the ones provided by the Q network service providers. Therefore, the strategy space of each customer u_k is the set of network service providers, and each candidate network service provider has a number of instances of SC_k of u_k, i.e., $\{sp_1, sp_2, \cdots, sp_Q\}$. On the other hand, network service provider sp_i makes its decision of where to implement request r_k in which cloudlet or data center in $\{\mathcal{CL} \cup \mathcal{DC}\}$. It also decides the price for the implemented request, such that its revenue is maximized. Notice that each location L_j in $\{\mathcal{CL} \cup \mathcal{DC}\}$ is considered as a candidate location of service provider sp_i, when sp_i has VMs in L_j. Let $\mathcal{L}_i$ be the candidate locations for sp_i, and let $\mathcal{VM}_{j,i}$ be the set of VMs of sp_i in location $L_j \in \mathcal{L}_i$. For each service chain SC_k, the strategy space of network service provider sp_i includes all locations in $\mathcal{L}_i$. Each player in the NFV market is selfish by maximizing its own revenue.

The aforementioned game can be considered as a *facility location game*, which is related to the facility location problem. The facility location problem deals with placing facilities in a network, and each facility serves a certain number of clients. In a facility location game, we have a set of selfish players wish into place facilities into a network with an objective of maximizing their own revenues.

E. Problem definitions

Given a NFV market that is based on a multi-tier cloud network $G = (\mathcal{CL} \cup \mathcal{DC}, E)$, Q network service providers offer their network services to customers, and there is a set of $\mathcal{R}$ NFV-enabled requests. We consider the following optimization problems in G.

Problem 1: *The social welfare maximization problem:* In a NFV market of a multi-tier cloud network G, we aim to maximize the social welfare of the market, subject to the constraints on available numbers of VMs in each location L_j in $\mathcal{CL} \cup \mathcal{DC}$ and the upload and download bandwidth requirements of each $VM_{j,m}$ of the VMs in location $L_j \in \mathcal{VM}_j$.

Problem 2: In real scenarios, NFV-enabled requests arrive into G one by one without the knowledge of their future arrivals. Also, the customers may deviate from their best strategies, and such information is usually not known to other customers and network service providers in the NFV market. *The online social welfare maximization problem with uncertainty* in G is to admit or reject each incoming NFV-enabled request immediately, with an aim to maximize the social welfare of the market, subject to the constraints on available numbers of VMs in each location L_j in $\mathcal{CL} \cup \mathcal{DC}$, and the upload and download bandwidth requirements of each $VM_{j,m}$ of the VMs in location $L_j \in \mathcal{VM}_j$.

IV. A Facility Location Game for the Social Welfare Maximization Problem

We present an efficient mechanism for the social welfare maximization problem.

A. Overview

The essence of the proposed mechanism is a multi-stage facility location game with network service providers and customers being strategic agents. Specifically, in the first stage, network service providers decide which cloudlets or data centers to implement NFV-enabled requests. In the second stage, service providers set the prices for consumers. And, in the last stage, each customer selects a network service provider and pays the specified price. We thus need to specify how prices are set and how requests are assigned to the candidate locations by each network service provider. The basic idea of our mechanism is to adopt a pricing mechanism that allow each player in the game to make its decision based on its true values for the service chains offered by network service providers. Also, we reduce the problem of assigning requests to VMs of each network service provider to a minimum weight perfect matching problem [17] in an auxiliary bipartite graph whose construction is as follows.

B. Mechanism

We now describe the detailed steps of the three stages of the mechanism: **stage 1**, location selection by each network service provider sp_i, **stage 2**, pricing by each network service provider sp_i for each customer, and **stage 3**, network service provider selection by each customer.

Stage 1. Given a set of candidate locations $\mathcal{L}_i$, each network service provider sp_i first decides locations for NFV-enabled requests. Recall that we assume each player in the game strategically makes its decisions based on its own revenue. From the network service provider's point of view, to maximize its own revenue given its limited number of VMs that are available in the multi-tier cloud network, it needs to admit a subset of requests that could lead the maximum revenue. To this end, we transfer the problem of locations choices by each network service provider sp_i to the problem of finding a minimum weight perfect matching in a bipartite graph $G' = (V', E')$.

We now construct the bipartite graph $G'_i = (V'_i, E'_i)$ for network service provider sp_i. Specifically, the node set V' of G' consists of two disjoint subsets, i.e., V'_a and V'_b. Each node in set V'_a corresponds a NFV-enabled request $r_k \in \mathcal{R}$, and each node in set V'_b denotes an available VM in $\cup_{L_j \in \mathcal{L}_i} \mathcal{VM}_{j,i}$ of network service provider sp_i. We add an edge between each node in V'_a and each node in V'_b, to represent an assignment of a NFV-enabled request r_k to a VM owned by network service provider sp_i, if the VM has enough upload and download bandwidths for the request. Let $(r_k, VM_{j,i})$ be the edge. Recall that the revenue received by sp_i due to serving request r_k is $p_{i,k} - \rho_k(c^p_{k,j} + c^b_{k,j})$. Since $p_{i,k}$ is not determined yet by the network service provider sp_i, to maximize its revenue is to minimize the cost of implementing request r_k, i.e., $\rho_k(c^p_{k,j} + c^b_{k,j})$. We thus consider the cost of assigning r_k to its $VM_{j,i}$ in location L_j as the weight of edge $(r_k, VM_{j,i})$ by

$$w(r_k, VM_{j,i}) = \rho_k(c^p_{k,j} + c^b_{k,j}). \tag{5}$$

It must be mentioned that $|V'_a|$ may not be equal to $|V'_b|$. If $|V'_a| \geq |V'_b|$, we add $|V'_a| - |V'_b|$ *dummy VM nodes* to V'_b. Each request node in V'_a connects to each dummy VM node, and the weight of the edge is set to infinity. Otherwise, we add $|V'_b| - |V'_a|$ *dummy request nodes* to V'_a. Fig. (2) shows an example of the proposed bipartite graph G'_i.

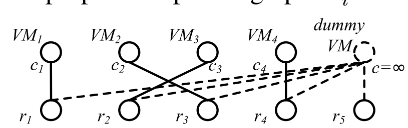


Fig. 2. An example of the constructed bipartite graph G'_i.

Having constructed graph G'_i, we find a minimum weighted perfect matching [17] M_i in G'_i that minimizes the cost of network service provider sp_i.

Given the perfect matching M_i for network service provider sp_i, each edge in M_i denotes a preference of sp_i of admitting the request. Let $\mathcal{R}_i$ be the set of requests assigned to the VMs of network service provider sp_i. Initially, $\mathcal{R}_i$ includes the requests that are included in matching M_i. Specifically, if all requests in $\mathcal{R}_i$ select sp_i, each of their implementation cost corresponds to the weight of matching M'_i.

Not all requests in $\mathcal{R}_i$ will select sp_i as they may have the other choices with lower implementation costs. Specifically, for each request $r_k \in \mathcal{R}_i$, we exclude it from $\mathcal{R}_i$, if there exists another network service provider $sp_{i'}$ with $i' \neq i$ that result in a lower implementation cost. Let $\mathcal{R}^{exd}_i$ be the set of excluded requests and $\mathcal{VM}_i^{exd}$ the corresponding set of VMs to which those requests in $\mathcal{R}_i^{exd}$ are assigned in matching M_i.

Given requests in $\cup_{i=1}^{Q}\mathcal{R}_i^{exd}$ that are excluded from the initial matching of network service providers, we repeat the above procedure until there is no excluded requests. So far, each request in $\mathcal{R}_i$ achieves its minimum implementation cost.

Stage 2. We now decide the pricing of the service chains offered by network service provider sp_i. Intuitively, to make each request r_k in $\mathcal{R}_i$ select sp_i, the price it sets for the request should not be higher than the network service provider achieving the second lowest implementation cost for it. This is the highest price that sp_i could expect to get away with charging request r_k; charging any more would give some network service provider $sp_{i'}$ an incentive to undercut sp_i. Note that we consider a scenario that all network service providers can obtain the implementation costs of requests in different locations, because the computing and bandwidth resource consumptions in edge clouds are usually public information. Finally we give the prices each network service provider set for the requests.

Stage 3. Each customer selects a network service provider with the lowest price to implement its request r_k.

Algorithm 1 provides a detailed procedure of the proposed mechanism for the social welfare maximization problem, which is referred to as `FLG_SWM`.

Algorithm 1 `FLG_SWM`

Input: A multi-tier cloud network $G = (\mathcal{CL} \cup \mathcal{DC}, E)$ and a set of NFV-enabled requests $\mathcal{R}$.

Output: The assignment of each request in $\mathcal{R}$ to a network service provider.

/***Stage (1)**: Location selection by each network service provider*/
$\mathcal{VM}_i \leftarrow \cup_{L_j \in \mathcal{CL} \cup \mathcal{DC}} \mathcal{VM}_{j,i}$; /*the set of available VMs of each network service provider sp_i*/
$\mathcal{R}^{adt} \leftarrow \mathcal{R}$; /*the set of to-be-admitted requests*/
while $\mathcal{VM}_i \neq \emptyset$ or $\mathcal{R}^{adt} \neq \emptyset$ **do**
  for each network service provider sp_i **do**
    if $\mathcal{VM}_i \neq \emptyset$ **then**
      $\mathcal{VM}_i^{exd} \leftarrow \emptyset$; /*The set of VMs that are excluded from the initial minimum weight matching in a bipartite graph G_i'*/
      Construct the bipartite graph $G_i' = (V_i', E_i')$ as illustrated in Fig. 2;
      Find a minimum weight perfect matching M_i in G_i';
      Exclude a matched pair of VM and request r_k in M_i, if the VM is not the first choice of r_k (i.e., there is another VM of another network service provider $sp_{i'}$ that can achieve a lower implementation cost for r_k);
      Add the excluded VM into $\mathcal{VM}^{exd}$, and the request into $\mathcal{R}_i^{exd}$;
      $\mathcal{VM}_i \leftarrow \mathcal{VM}^{exd}$;
  If there exists a request in $\cup_{i=1}^{Q}\mathcal{R}_i^{exd}$ that considers a VM in $\mathcal{VM}_i$ as its best choice (the VM that can achieve the minimum implementation cost), $\mathcal{R}^{adt} \leftarrow \cup_{i=1}^{Q}\mathcal{R}_i^{exd}$;
  Otherwise, $\mathcal{R}^{adt} \leftarrow \emptyset$;
/***Stage (2)**: Pricing by each network service provider*/
For each network service provider sp_i, set its price for request r_k as the cost of implementing r_k in a VM by another network service provider that has the second lowest implementation cost;
/***Stage (3)**: Service provider selection by each customer*/
Each customer selects its best response strategy, by choosing the network service provider with the lowest price to implement its NFV-enabled request r_k;

C. Algorithm analysis

In the following we analyze the economic properties and performance of the proposed mechanism.

Lemma 1: The proposed facility game for the social welfare maximization problem in a NFV market under a multi-tier cloud network G is incentive compatible.

Proof: Showing the lemma is to show that each customer and each network service provider have incentives to participate in the game by gaining non-negative revenues.

For each customer u_k, it has a value for each service chain SC_k provided by network service provider sp_i, which is denoted by $\pi_{i,k}$. For its NFV-request r_k, it gathers a revenue of $\Delta_k = \pi_{i,k} - p_{i,k}$, if SC_k is implemented in a VM of network service provider sp_i. Since we assume that a customer only buys an implementation of its service chain of service provider sp_i if $\pi_{i,k} \geq p_{i,k}$, and it pays $p_{i,k}$, so the mechanism is incentive-compatible. On the other hand, for each network service provider sp_i, its revenue depends on the prices it sets for requests and the cost of implementing its admitted requests. Recall that the price it sets for each request r_k the requests is no higher than the network service provider that achieves the second lowest implementation cost for request r_k. This makes the customer to consider sp_i as its best choice, leading to a non-negative revenue. The game thus is incentive-compatible for network service providers as well. ■

Lemma 2: The proposed mechanism for the social welfare maximization problem is a potential game with potential function $\Phi_{Q,N}$.

Proof: We first introduce the definition of a potential game: for any finite game, a potential game Φ is a function that maps every strategy S to some a real value that satisfies the following condition: If $S \subset (S_1, S_2, \cdots, S_k)$, $S_i' \neq S_i$ is an alternate strategy for some player i, and $S' = (S_{-i}, S_i')$, then $\Phi(S') - \Phi(S) = u_i(S') - u_i(S)$, where $u_i(S)$ is the utility of player i under strategy S.

Showing that the game is a potential game, we need to show that if a network service provider sp_i changes its selected VM to implement NFV-enabled requests, then the change in social welfare $\Phi_{Q,N}$ is exactly the change in sp_i's welfare. To show this, imagine that sp_i chooses to "drop out of the game". If network service provider sp_i drops out, each NFV-enabled request r_k that was served by sp_i switches to its second best choice. Recall that $p_{i,k}$ is exactly the cost of the second best choice. Thus, the NFV-enabled request r_k will be served at cost $p_{i,k}$, rather than its previous cost $\rho_k(c_{k,j}^p + c_{k,j}^b)$, so the increase in cost is $p_{i,k} - \rho_k(c_{k,j}^p + c_{k,j}^b)$, exactly the revenue of network service provider sp_i. The facility game thus is a potential game. ■

Lemma 3: The proposed facility game has the following three properties:

- **Property (1)**: $\Phi_{Q,N}(S)$ is submodular: for any strategy set $S \subset S' \subset A$ and any element s in A, we have $\Phi_{Q,N}(S+s) - \Phi_{Q,N}(S) \geq \Phi_{Q,N}(S'+s) - \Phi_{Q,N}(S')$
- **Property (2)**: The total value for all players is less than or equal to the total social welfare $\Phi_{Q,N}$
- **Property (3)**: The value for one player is at least its added value for the society: $\alpha(s_i) \geq \Phi_{Q,N}(S) - \Phi_{Q,N}(S - s_i)$.

Proof: **Property (2)** is essentially met by the definition of the social welfare maximization problem.

We first show **Property (1)**. Recall that the social welfare of the facility game consists of the revenues of both network service providers and customers, i.e., $\Phi_{Q,N} = \sum_{i=1}^{Q}\delta_i + \sum_{k=1}^{N}\Delta_k$. The strategy set for network service providers is the set of locations to instantiate VNF instances. Let S_{sp} be their selected set of locations to serve customers in a NE. To show that $\sum_{i=1}^{Q}\delta_i$ is submodular, we need to show that the marginal benefit to $\sum_{i=1}^{Q}\delta_i$ is diminishing as more locations are added into S_{sp} to serve the customers. It must be mentioned that in the proposed mechanism, the network service providers and customers are matched via a bipartite matching, and the prices of each network service provider sp_i asked is independent of the location selection. This means that the price each network service provider sets for each customer is independent of the locations it selects. Let $L_{j'}$ be the location that is to be added into S. We assume that $L_{j'}$ is a better solution for a request compared with those in S. By re-writing Eq. (4), we have

$$\begin{aligned}\Phi_{Q,N}(S) &= \sum\nolimits_{i=1}^{Q}\delta_i + \sum\nolimits_{k=1}^{N}\Delta_k\\ &= \sum_{L_j\in S_{sp}}\sum_{r_k\in R_j}\Big(\pi_{i,k} - p_{i,k} + p_{i,k} - \rho_k(c^p_{k,j} + c^b_{k,j})\Big)\\ &= \sum\nolimits_{L_j\in S_{sp}}\Big(\sum\nolimits_{r_k\in R_j}\pi_{i,k} - \rho_k(c^p_{k,j} + c^b_{k,j})\Big)\end{aligned}$$

where R_j is the set of requests that are assigned to location L_j. Similarly, we have

$$\begin{aligned}&\Phi_{Q,N}(S'\cup\{L_{j'}\})\\ &= \sum\nolimits_{L_j\in S_{sp}\cup\{L_{j'}\}}\Big(\sum\nolimits_{r_k\in R_j}\pi_{i,k} - \rho_k(c^p_{k,j} + c^b_{k,j})\Big)\\ &= \Phi_{Q,N}(S) + \pi_{i,k} - \rho_k(c^p_{k,j'} + c^b_{k,j'})\\ &\qquad - \big(\pi_{i,k} - \rho_k(c^p_{k,j} + c^b_{k,j})\big)\\ &= \Phi_{Q,N}(S) - \rho_k(c^p_{k,j'} + c^b_{k,j'}) + \rho_k(c^p_{k,j} + c^b_{k,j}) \end{aligned}\tag{6}$$

and

$$\begin{aligned}\Phi_{Q,N}(S' + L_{j'}) = \Phi_{Q,N}(S') &- \rho_{k'}(c^p_{k',j'} + c^b_{k',j'})\\ &+ \rho_{k'}(c^p_{k',j} + c^b_{k,j}),\end{aligned}\tag{7}$$

where $r_{k'}$ is another request whose implementation cost can be improved by adding location $L_{j'}$ to the location set S'. It is clear that the saving in the implementation cost for request r_k is higher than that of request $r_{k'}$; otherwise, request $r_{k'}$ will be assigned to $L_{j'}$ instead of r_k. Therefore, we have

$$\begin{aligned}&\rho_{k'}(c^p_{k',j} + c^b_{k',j}) - \rho_{k'}(c^p_{k',j'} + c^b_{k',j'})\\ &\leq \rho_k(c^p_{k,j} + c^b_{k,j}) - \rho_k(c^p_{k,j'} + c^b_{k,j'}),\end{aligned}\tag{8}$$

which also means that $\Phi_{Q,N}(S' + L_{j'}) - \Phi_{Q,N}(S') \leq \Phi_{Q,N}(S + L_{j'}) - \Phi_{Q,N}(S)$.

We then show **Property (3)**. Here we need to show that for all strategy vector S and any player s_i, we have $\alpha(s_i) \geq \Phi_{Q,N}(S) - \Phi_{Q,N}(S - s_i)$. Assume that we consider a player as a network service provider, we have $\alpha(s_i) \geq \Phi_{Q,N}(S) - \Phi_{Q,N}(S - s_i)$, as the exclusion of network service provider sp_i leads to the reduction of its own revenue and also the revenue of other customers. On the other hand, the exclusion of any customer from the game leads to a social welfare reduction that is equal to the customer's revenue. ∎

Theorem 1: The best response dynamics of the proposed mechanism `FLG_SWM` converge to a pure strategy equilibrium, and its PoA is at most 2.

Proof: Recall that $\Phi_{Q,N}$ is the social welfare delivered by the proposed facility game. As shown in Lemma 2, we use $\Phi_{Q,N}$ as the potential game for the game. Let S be a pure strategy vector minimizing $\Phi_{Q,N}(S)$. Consider any move by network service provider sp_i that results in a new strategy vector S'. By assumption, $\Phi_{Q,N}(S') \geq \Phi_{Q,N}(S)$, and by Lemma 2, $\delta_i(S') - \delta_i(S) = \Phi_{Q,N}(S') - \Phi_{Q,N}(S)$. Thus, sp_i's revenue can not increase from this move, and hence S is stable. Note that any strategy S with the property that $\Phi_{Q,N}$ cannot be decreased by altering any one strategy in S is a NE. Furthermore, the best response dynamics simulates local search on $\Phi_{Q,N}$, improving moves for players decreases the value of the potential function. This means that the best response dynamics converge to a NE.

We show the quality of the NE. Let S be the set of locations selected by all network service providers at the NE. Denote by OPT the set of locations for the socially optimal solution, and let O be the corresponding strategy space. We first note, by monotonicity, that $\Phi_{Q,N}(O) \leq \Phi_{Q,N}(S\cup O)$. O^i be the strategies selected by the first i network service providers in the socially optimal solution OPT. We have

$$\begin{aligned}&\Phi_{Q,N}(O) - \Phi_{Q,N}(S) \leq \Phi_{Q,N}(O\cup S) - \Phi_{Q,N}(S)\\ &= \sum\nolimits_{i}^{Q}\Big(\Phi_{Q,N}(S\cup O^i) - \Phi_{Q,N}(S\cup O^{i-1})\Big).\end{aligned}\tag{9}$$

By **Property (1)**, we have

$$\begin{aligned}&\Phi_{Q,N}(S\cup O^i) - \Phi_{Q,N}(S\cup O^{i-1})\\ &\leq \Phi_{Q,N}(S + o_i - s_i) - \Phi_{Q,N}(S - s_i),\end{aligned}\tag{10}$$

for all network service provider sp_i. Using **Property (3)**, we can further bound inequality (10) by $\alpha_i(S + o_i - s_i) \leq \alpha_i(S)$, considering that S is an equilibrium. Together, we have $\Phi_{Q,N}(O) - \Phi_{Q,N}(S) \leq \Phi_{Q,N}(O\cup S) - \Phi_{Q,N}(S) \leq \sum_i^Q \alpha_i(S)$. Due to **Property (2)**, $\sum_i^Q \alpha_i(S) \leq \Phi_{Q,N}(S)$, we thus have $\Phi_{Q,N}(O) \leq 2\Phi_{Q,N}(S)$, which means that the PoA of the proposed mechanism is at most 2. ∎

V. Online Learning Algorithm for the Dynamic Social Welfare Maximization Problem with Uncertainty

We now consider the online social welfare maximization problem with uncertain customer strategies.

A. Overview

Although network service providers may not have the complete information of customers, they may learn the behaviors of customers in terms of service selections. However, they may not do that themselves, and resort to third parties that serves as 'experts' on customers behavior. Specifically, we assume that there are several experts in the NFV market. They serve as trustworthy third parties that collects and learns customers' distributions of service selection. Each of such expert recommends a set of customers to the network service providers. The network service provider however may not fully trust experts, by dynamically evaluating the experts. Given such a NFV market, we handle the uncertainties of the distributions of customers' values on network services via leveraging the technique of multi-armed bandits with experts. That is, experts predict the values of customers for each type of service chains. They then feed such predicted information to the proposed online learning algorithm. The proposed algorithm then decides the prices of each instance of service chains of network service providers, by invoking algorithm `FLG_SWM`. The real values of customers are then revealed, and the costs of network service providers and experts are calculated.

B. Online learning algorithm

We now describe the proposed online algorithm. We assume that there are Y experts in the multi-tier cloud network G. Each expert is considered as an arm, and each expert is in charge of a subset of arms in G. Without loss of generality, each expert will always recommend its arms by predicting their values for the services of network service providers. Each expert recommends its arms (customers) by revealing its learnt value of each customer for each instance of service chains of all network service providers, and receives a cost if its recommendation deviates from the real values of customers.

Let exp_n be an expert, with $1 \leq n \leq Y$. Initially, the algorithm assigns each expert a weight of 1, meaning a full trust of the predicted values of its customers for all service chain instances. As the algorithm proceeds, it degrades the weight of each expert according to the cost (a.k.a penalty) received by the expert. To determine which customers to select in the game, we select an expert and its responsible customers with a probability that is proportional to the weight of the expert. Denote by $w_r(exp_n)$ be the current weight of expert exp_n in the current round r, and $p_r(exp_n)$ be the probability of choosing expert exp_n in round r, we then have

$$p_r(exp_n) = w_r(exp_n)/(\sum_{n'=1}^{Y} w_r(exp_{n'})). \qquad (11)$$

The selected expert and its customers will be allowed to participate in the game in the current round. We then invoke algorithm `FLG_SWM`, by considering the chosen customers and all network service providers as the input. Algorithm `FLG_SWM` then returns the pricing of network service providers and customer's selection of services, based on the predicted values of experts. Once the customers select their network service providers, their values will be released. Recall that the value of customer u_k for the services of provider sp_i is denoted by $\pi_{i,k}$, and it only selects a network service provider when $\pi_{i,k} \geq p_{i,k}$. Let $\hat{\pi}_{i,k}$ be the predicted value of customer u_k by expert exp_n. The social welfare may be reduced to the inaccurate predictions of $\pi_{i,k}$ of each exp_n. We thus define the penalty received by each expert exp_n as the reduced revenue based on the predicted value, i.e.,

$$\begin{aligned} c_r(exp_n) &= \sum_{i=1}^{Q} \delta_i + \sum_{k=1}^{N_r} \Delta_k - \sum_{i=1}^{Q} \delta_i - \sum_{k=1}^{N_r} \hat{\Delta}_k, \\ &= \sum_{k=1}^{N_r} \left(\Delta_k - \hat{\Delta}_k\right). \qquad (12) \end{aligned}$$

where N_r is the number of customers that are selected to participate the game, and $\hat{\Delta}_k = \hat{\pi}_{i,k} - p_{i,k}$ if u_k selects network service provider sp_i. To avoid such reduction of social welfare caused by the selection of experts and their customers, we decrease the weight of expert exp_n after round r by

$$w_{r+1}(exp_n) = w_r(exp_n) \cdot (1-\epsilon)^{c_r(exp_n)}, \qquad (13)$$

The detailed steps of the proposed algorithm are elaborated in **Algorithm** 2, which is referred to as **Algorithm** `OL_FLG`.

Algorithm 2 `OL_FLG`

Input: $G = (\mathcal{CL} \cup \mathcal{DC}, E)$, a set of NFV-enabled requests.
Output: An assignment of each request to either a cloudlet or datacenter for processing.

Initialize the weights of experts as $w_1(exp_n) = 1$ for the expert exp_n in time slot 1;
for each round $r \leftarrow 1 \ldots T$ **do**
  Calculate the probability $p_r(exp_n)$ of selecting an expert exp_n by Eq.(11);
  Select each expert exp_n with probability $p_r(exp_n)$;
  Each selected expert predicts the values of its customers;
  Invoke **Algorithm** `FLG_SWM`;
  In the end of round r, observe the costs of experts, and update its weight by Eq.(13);

C. Regret analysis

Theorem 2: Algorithm `OL_FLG` has a regret of $\frac{\ln T}{\epsilon} + 2\epsilon U_d$, assuming that there is a bound on the minimum and maximum values of each customer, let U_d be this bound, i.e., $U_d = \pi_{max} - \pi_{min}$, where $\pi_{max} = \max_{i,k} \pi_{i,k}$ and $\pi_{min} = \min_{i,k} \pi_{i,k}$.

Proof: We first give the definition of regret of following the predictions of experts in the NFV market of the multi-tier cloud network. Considering that online social welfare maximization problem in the multi-tier cloud network is to maximize the revenue of customers and service providers, we define the regret as the expected deviation of the social welfare of the obtained solution from the optimal solution in each round by $Reg(T) = \Phi(\texttt{OL\_FLG}) - E[\Phi_{n^*}]$, where $\Phi(\texttt{OL\_FLG})$ is the social welfare obtained by algorithm `OL_FLG` and Φ_{n^*} is the social welfare that is obtained based on the predictions of the best expert exp^* of the Y experts. The total cost $cost(exp_n)$ of each expert exp_n is $\sum_{r=1}^{T} c_r(exp_n)$, we then have $exp^* \in \arg\min_{1 \leq n \leq Y} cost(exp_n)$, and its cost is denoted by $cost^*$.

Recall that algorithm `OL_FLG` dynamically adjusts its weight of each weight according to the penalty of the expert. Basically, an expert with a higher penalty will receive a lower weight (corresponding to less trust).

Let $W_r = \sum_{n=1}^{Y} w_r(exp_n)$ be the total weight before round r. The weight of each expert after round T then is $w_{T+1}(exp_n) = w_1(exp_n)\Pi_{r=1}^{T}(1-\epsilon)^{cost(exp_n)}$. The total weight after round T is

$$W_{T+1} > w_{T+1}(exp^*) = (1-\epsilon)^{cost^*} > (1-\epsilon)^{\Phi_{n^*}}, \quad (14)$$

due to the definition of costs and the fact that $(1-\epsilon)^a > (1-\epsilon)^b$ for any positive values of a and b with $a < b$.

We first show the relation between the costs received by experts and the social welfare of all players in the game.

$$\begin{aligned} W_{r+1}/W_r &= (\sum_{n=1}^{Y} w_{r+1}(exp_n))/W_r \\ &= (\sum_{n=1}^{Y}(1-\epsilon)^{c_r(exp_n)} w_r(exp_n))/W_\tau, \text{due to Eq. (13)} \quad (15) \end{aligned}$$

$$
\begin{aligned}
&< \sum\nolimits_{n=1}^{Y}(1-\alpha c\tau(exp_n)+\beta c_\tau(exp_n)^2)\cdot p_\tau(exp_n),\\
&\quad \text{since } W_\tau \geq 1\\
&\quad \text{and } \exists \alpha,\beta>0,\ (1-\epsilon)^x < 1-\alpha x+\beta x^2 \text{ for all } x>0.\\
&= \sum\nolimits_{n=1}^{Y} p_r(exp_n) - \alpha \sum\nolimits_{n=1}^{Y} p_r(exp_n) c_r(exp_n)\\
&\qquad\qquad + \beta \sum\nolimits_{n=1}^{Y} p_r(exp_n) c_r(exp_n)^2 \qquad (16)\\
&= 1-\alpha \sum\nolimits_{n=1}^{Y} p_r(exp_n) \sum\nolimits_{k=1}^{N_r}(\Delta_k-\hat{\Delta}_k)\\
&+\beta \sum\nolimits_{n=1}^{Y} p_\tau(exp_n)\Big(\sum\nolimits_{k=1}^{N_r}(\Delta_k-\hat{\Delta}_k)\Big)^2\\
&< 1-\alpha \sum_{n=1}^{Y} p_r(exp_n) \sum_{k=1}^{N_r}\Big(\sum_{i=1}^{Q}\delta_i+\Delta_k-\big(\sum_{i=1}^{Q}\delta_i+\hat{\Delta}_k\big)\Big)\\
&+\beta \sum_{n=1}^{Y} p_\tau(exp_n)\Big(\sum\nolimits_{i=1}^{Q}\delta_i+\Delta_k-\big(\sum\nolimits_{i=1}^{Q}\delta_i+\hat{\Delta}_k\big)\Big)^2\\
&< 1-\alpha \sum\nolimits_{n=1}^{Y} p_r(exp_n) \sum\nolimits_{k=1}^{N_r} \sum\nolimits_{i=1}^{Q}(\delta_i+\Delta_k)\\
&+\beta \sum\nolimits_{n=1}^{Y} p_\tau(exp_n)\Big(\sum\nolimits_{i=1}^{Q}(\delta_i+\Delta_k)\Big)^2\\
&= 1-\alpha E(\Phi(\texttt{OL\_FLG},r))+\beta E(\Phi(\texttt{OL\_FLG},r)^2), \qquad (17)
\end{aligned}
$$

where $\Phi(\texttt{OL\_FLG}, r)$ is the total social welfare in round r, clearly we have $\Phi(\texttt{OL\_FLG}) = \sum_{r=1}^{T}\Phi(\texttt{OL\_FLG}, r)$.

By taking a logarithm on the above inequality, we have

$$
\begin{aligned}
&\ln(W_{\tau+1}/W_\tau)\\
&< \ln(1-\alpha E(\Phi(\texttt{OL\_FLG},r))+\beta E(\Phi(\texttt{OL\_FLG},r)^2))\\
&< -\alpha E(\Phi(\texttt{OL\_FLG},r))+\beta E(\Phi(\texttt{OL\_FLG},r)^2), \qquad (18)
\end{aligned}
$$

since $\ln(1-x) < -x$ for any $x \in (0,1)$. In particular, this holds when $(\alpha,\beta)=(\epsilon,0)$.

Considering all rounds with $1 \leq r \leq T$, we have

$$
\begin{aligned}
&\sum\nolimits_{r=1}^{T}(\alpha E(\Phi(\texttt{OL\_FLG},r))-\beta E(\Phi(\texttt{OL\_FLG},r)^2))\\
&< -\ln(W_{r+1}/W_r) < -\ln \Pi_{r=1}^{T}(W_{r+1}/W_r)\\
&= -\ln(W_{r+1}/W_r) = \ln W_1 - \ln W_{T+1}\\
&< \ln T - \ln(1-\epsilon)\Phi_{n^*}. \qquad (19)
\end{aligned}
$$

With $(\alpha,\beta)=(\epsilon,0)$, we have

$$E(\Phi(\texttt{OL\_FLG})) < \ln T/\epsilon + (1/\epsilon)\ln[1/((1-\epsilon))]E(\Phi_{n^*}).$$

Assuming that $\epsilon \in (0,1/2)$, we have $\frac{1}{\epsilon}\ln\frac{1}{(1-\epsilon)} \leq 1+2\epsilon$, which means

$$E(\Phi(\texttt{OL\_FLG})-\Phi_{n^*}) < \ln T/\epsilon + 2\epsilon E(cost^*). \qquad (20)$$

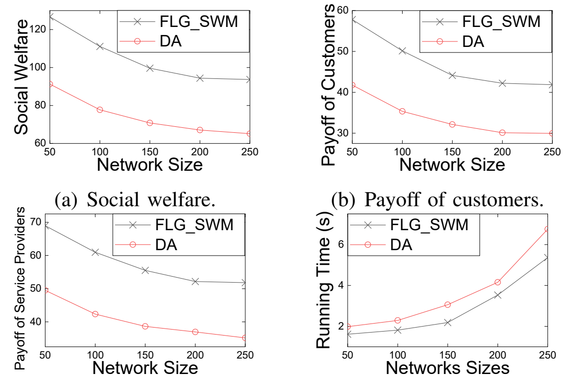
Clearly we have $cost^* < U_d$. The regret of algorithm `OL_FLG` thus is $E(\Phi(\texttt{OL\_FLG})-\Phi_{n^*}) < \ln T/\epsilon + 2\epsilon U_d$. ■

VI. Experiments

We now evaluate the performance of the proposed algorithms via both simulations and test-bed implementations.

A. Experiment Settings

We consider multi-tier cloud networks by varying their sizes from 50 to 200 switch nodes and 5 data centers, where each network topology is generated using GT-ITM [41]. The number of cloudlets in the mobile edge network is set to 10% of the network size, which are randomly distributed in the network edge. We also use a real network topologies AS1755 from [16]. The numbers of VMs provided by each cloudlet and data center are randomly generated from [10, 15] and [15, 50], respectively. The bandwidth capacity of each VM is drawn from the range of [10Mpbs, 100Mbps]. Each NFV-enabled request demands a service chain containing at most 5 VNFs, picked among Firewall, Proxy, NAT, IDS, and Load Balancing (LB). The costs of transmitting and processing 1 GB of data are set within [$0.05, $0.12] and [$0.15, $0.22]. The pre-defined threshold of revenue decreases ϑ is set 20%. The traffic volume of each request is randomly drawn from $[10, 200]$ Megabytes. The running time of each algorithm is obtained based on a machine with a 3.70GHz Intel i7 Hexa-core CPU and 16 GiB RAM. Unless otherwise specified, these parameters will be adopted in the default setting.



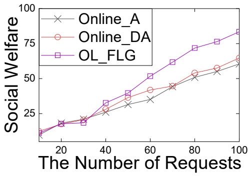
(a) Social welfare. (b) Payoff of customers. (c) Payoff of service providers. (d) Running time.

Fig. 3. The performance of algorithms `FLG_SWM` and `DA`

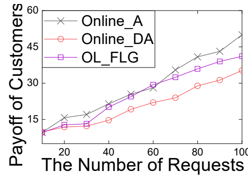
We evaluate the performance of the proposed algorithms against the following benchmarks. We first consider the double auction of [4]. In the mechanism, potential customers submit their bids and potential service providers simultaneously submit their ask prices to an auctioneer, and then the auctioneer chooses some price that clears the market: all the sellers who asked less than the chosen price sell and all buyers who bid more than the chosen price buy at this chosen price. The offline and online versions of this double auction mechanism are referred to as `DA` and `Online_DA`, respectively. We then consider an online auction in [20]. In the auction, customers calculate the payoffs of potential service providers based on their true value, and choose the service provider with the highest payoff. We refer to this benchmark as `Online_A`.

B. Performance of the facility location game `FLG_SWM`

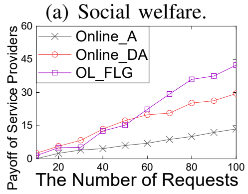
We first evaluate the performance of algorithm `FLG_SWM` against that of algorithm `DA`, in terms of the social welfare, payoff of customers, payoff of service providers, and the running time, in GT-ITM generated networks with their sizes varied from 50 to 250. Fig. 3 shows the results can see from Fig. 3 (a) that the social welfare achieved by `FLG_SWM` is higher than that of `DA`. The reason is that in `DA`, the trade



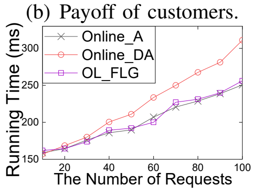
(a) Social welfare.



(b) Payoff of customers.



(c) Payoff of service providers.



(d) Running time.

Fig. 4. The performance of algorithms `OL_FLG`, `Online_A`, and `Online_FLG`

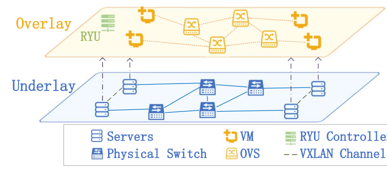
between a bidder and an asker happens as long as the bid is greater than the ask. In contrast, `FLG_SWM` finds an optimal matching between buyers and sellers, by finding a minimum weighted perfect matching in the constructed auxiliary graph with dummy nodes, as shown in Fig. 2. We can also see that the social welfare decreases with the growth of the network size from 50 to 200, and then keeps stable afterwards when the network size increases from 200. The rationale behind is that a larger network size means a higher cost for service providers to implement each request. However, as the mechanism is incentive compatible the payoff of each provider will never be negative. Therefore, the payoff is stable when the network size is increased from 200. Similar patterns of payoffs can be seen in from Fig. 3(b) and Fig. 3(c). From Fig. 3(d), we can see that `FLG_SWM` has a lower running time than `DA`, since `DA` spends much time in messaging among different players.

C. Performance of the online learning algorithm `OL_FLG`

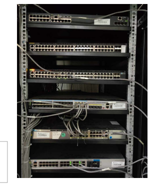
We then compare the performance of algorithm `OL_FLG` against that of algorithms `Online_A` and `Online_DA` in terms of the social welfare, payoff of customers, payoff of service providers, and running times, in a GT-ITM generated network with network size of 200. The social welfare achieved by `OL_FLG`, `Online_A` and `Online_DA` are shown in Fig. 4 (a). We can see from the figure that `OL_FLG` consistently delivers a higher social welfare than those by `Online_A` and `Online_DA`, because it learns request arrivals via a reinforcement learning process. The payoffs of customers and service providers are shown in Fig. 4 (b) and Fig. 4 (c), we can see from the figure that they consistently have a nonnegative payoff. We can also see from the figure that `Online_A` always provides higher payoffs of customers than `Online_DA` and `OL_FLG`, since it chooses the customers' payoffs maximization strategy that greatly reduces the payoffs of service providers.

D. Performance evaluation in a test-bed

We evaluate the performance of the online games in a real test-bed with five hardware switches, as shown in Fig. 5 (b). To testify the scalability of the proposed online game, we adopt a two-layered network architecture: an underlay and an overlay. The underlay is a network that interconnects five physical switches, and five servers with each having an i7-8700 CPU and 16G RAM. Based on this underlay, an overlay with an AS1755 topology is built based on VXLAN and Open vSwitch (OVS) [26]. All other settings are the same as the simulations.

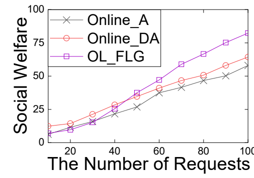


(a) Overlay and underlay of the test-bed.

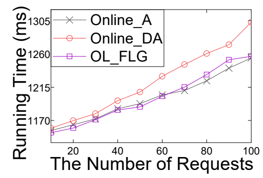


(b) Physical switches.

Fig. 5. The test-bed.



(a) Social welfare.



(b) Running time.

Fig. 6. The performance of algorithms `Online_FLG`, `Online_A`, and `Online_DA` in the test-bed.

Fig. 6 shows the performance of algorithms `OL_FLG`, `Online_A` and `Online_DA` in terms of social welfare and running times, in the test-bed. It can be seen that algorithm `OL_FLG` delivers much better social welfare than those of algorithms `Online_A` and `Online_DA`. For example, when there are 80 requests, `OL_FLG` has around 23.82% higher social welfare than that of `Online_A` and `Online_DA`.

VII. Conclusion

In this paper, we studied the social welfare maximization problems in a NFV market in a multi-tier cloud network. We first devised an efficient incentive-compatible mechanism and analyzed the existence of a Nash equilibrium for the social welfare maximization problem. We then designed a method based on multi-armed bandit for the dynamic social welfare maximization problem without the knowledge of future request arrivals and with uncertain customer payoffs, which allows network service providers to make their decisions with bounded regrets. We finally evaluated the performance of the proposed mechanisms by both simulations and test-bed implementations, base on synthetic and real network topologies. Results show that the performance of the proposed mechanisms obtain 23% higher social welfare than existing studies in the test-bed.

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