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Elastic Scheduling for Scaling Virtual Clusters in Cloud Data Center Networks

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ABSTRACT Data Center Networks (DCNs) have become more extensively applied in cloud computing in recent years. One important mission for DCNs is satisfying the fluctuation of on-demand resources for tenants. During the scaling of Virtual Clusters (VCs), existing works fail to fully consider placement techniques and the elasticity of the physical resource in the DCN at the same time. To address this, we use elasticity to measure the scaling potential of VCs in terms of both computation and communication resources. In this paper, we consider elastic scaling for existing VCs to maximize elasticity with the constraint of communication cost in the DCN. We achieve this through a resource allocation scheme, VCS, which comes with provable optimality guarantees for single VC scaling. After that, we extend our scheme for the scaling of multiple VCs, and we prove that scaling multiple VCs for the over-time elasticity maximization problem is NP-hard. Based on that, we present the MVCS algorithm for offline multiple VC scaling, which can maximize over-time elasticity during a stable time period. Furthermore, we propose two heuristic algorithms, S-OMVCS and A-OMVCS, using Bayesian parameter estimation to solve an online scaling with both synchronous and asynchronous incoming rates. Extensive simulations demonstrate that our elastic VC scaling placement schemes outperform existing state-of-the-art methods in terms of flexibility in the DCN.

INDEX TERMS Data center networks (DCNs), elastic scaling, Virtual Cluster (VC), optimization, Virtual Machine (VM) placement.

I. INTRODUCTION

Data Center Networks (DCNs) have become more extensively applied in cloud computing in recent years. Applications based on the cloud generate a significant amount of network traffic, and a considerable fraction of their runtime is due to network activity [1]. As reported in [2], [3], the resource available to tenants varies over time in EC2. One major problem for cloud computing tenants is lack of performance guarantee, which includes both resource limitations and unpredictable application demands.

To illustrate this, we show the average CPU utilization for the word count application in Hadoop (based on EC2 of Amazon [4]). We use four nodes to run this application: three slaves (orange, light green, and green lines) and one master (blue line). It is a three hours tracing result of the CPU utilization for these three slaves. We observe from Figure 1 that the word count application utilizes the CPU of the master node only during the map part of the execution (during the shuffle phase of the blue line). The three slaves (reduce phase) require very little resource. For each slave, the amount of resources required is time-varying. Since the configurations of slaves are different, resource inefficiencies may be encountered during the running period, as shown in the last hour in Fig. 1. Therefore, efficiently provisioning network resource for elastic scaling virtual clusters in the cloud is a critical issue.

We propose an elastic placement strategy to deal with resource scaling for the existing Virtual Clusters (VCs) in the DCN. A set of Virtual Machines (VMs) that connect one virtual switch is defined as a VC. Each VC not only has computing requirements but also requires communications among itself to complete the specified tasks for the applica-

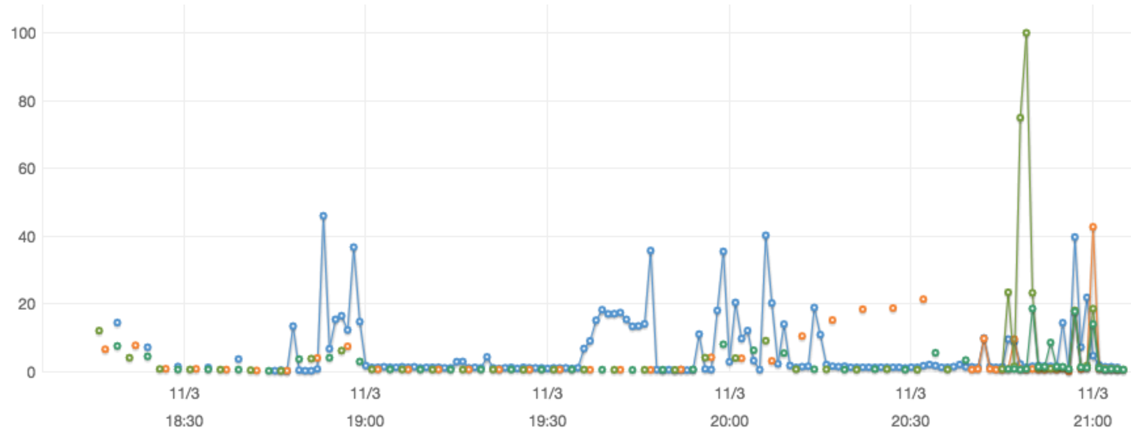

FIGURE 1. An example of tracing result for word count application on CPU utilizations.

tions. We use elasticity [5] to measure the growth potential of a VC placement for both computation and communication. We denote this as Physical Machine (PM) elasticity and Physical Link (PL) elasticity. Our objective is to maximize the elasticity during the placement of the VCs' scaling requests in the DCN under the resource and communication cost constraints. This paper is based on existing DCN architecture: a fat-tree. The capacities of PMs are slotted, and each slot can only host one VM, as shown in Fig. 2. The communication between VMs occurs through the PLs of each VC. The corresponding communication demands are determined by VM communication models. This paper uses the hose model, a communication model used to calculate bandwidth demand for VMs.

To maximize the elasticity in the DCN under the hose communication model, we face one important challenge: balancing the trade-off between communication cost and elasticity during the VC placement while guaranteeing both computation and communication resource scaling for one VC under the DCN. Take Fig. 2 as an example; VC1 has 7 existing VMs. We assume the upper bound of the subtree root is in the aggregation switch level. The scaling request for VC1 is from 5 VMs. One extreme assignment for the scaling request is to concentrated place all the scaling VMs into the PMs M_1 and M_2 under the switch S_{11}, as shown in Fig. 2 (a). This solution can save communication cost between existing VMs and incoming ones. However, the elasticity of VC1 decreases to 0, creating two bottleneck PMs, M_1 and M_2, with no scaling potential. Another extreme assignment is placing the VMs dispersedly, as shown in Fig. 2 (b). In this case, the elasticity of VC1 will be $\min\{\frac{2}{5}, \frac{2}{5}, \frac{3}{5}, \frac{3}{5}, \frac{4}{5}, \frac{4}{5}\} = \frac{2}{5}$. However, the communication cost under this assignment has already moved beyond the upper bound of the subtree root, which can not guarantee QoS for the users. To balance the trade-off between communication cost and elasticity, we try to find a solution between the two extreme assignments. In this paper, we propose an optimal solution that makes a placement based on the proportion of the remaining available capacities for the scaling request under the limitation of communication cost, as shown in Fig. 2 (c). Then, we extend our solution to the online multiple VC scaling placement problem, which is solved by a heuristic method with prediction. Our algorithm can improve over-time elasticity using historical knowledge and distribution to place the current scaling VCs.

In this paper, we jointly consider the placement and elasticity adjustment problems for scaling VCs to maximize elasticity with the constraint of communication cost in the DCN. Our contributions can be summarized as follows:

- We show that there is a trade-off between elasticity and communication cost for a VC scaling request. Given one scaling request, the decreasing placement of the elasticity may lead to an increase in the communication cost. We prove the bound for the extra cost, and we discuss the existence of an optimal solution during the elasticity adjustment.
- We propose an algorithm, VCS, for the scaling request of an existing VC under the constraints of resource and communication costs, and we prove that it is an optimal solution.
- We extend the single VC scaling placement problem for multiple VCs. We also prove that it is NP-hard, and we propose the MVCS algorithm for scaling resource during a stable time period to maximize the over-time elasticity of VCs.
- We describe the online condition for the multiple VC scaling problem with both synchronous and asynchronous incoming rates, and we propose two heuristic algorithms, S-OMVCS and A-OMVCS using the Bayesian parameter estimation.
- We conduct various simulations to compare our joint optimization method with other state-of-art approaches. The results are shown from different perspectives to provide conclusions.

The remainder of this paper is organized as follows. Section II surveys related works. Section III describes the model and then formulates the problem. Section IV investigates

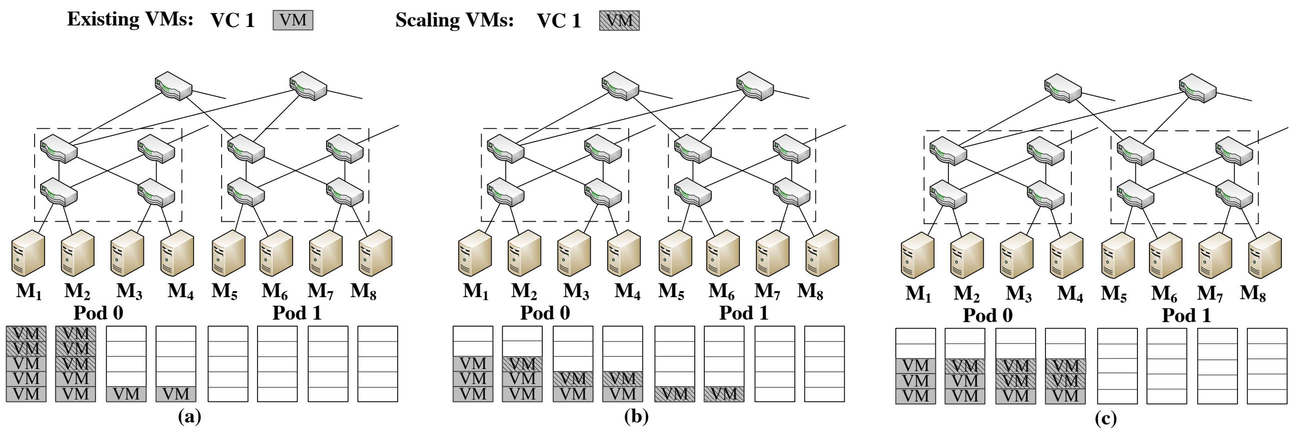

FIGURE 2. An example of different placements for single virtual cluster scaling.

elastic scaling for a single VC, and it proposes an optimal solution. Sections V and VI extend the problem into elastic scaling for multiple VCs and propose two heuristic algorithms for offline and online conditions. Section VII includes the experiments. Finally, Section VIII concludes the paper.

II. RELATED WORK

There are tremendous works about resource allocation for VC scaling. It is a technique of crucial importance, which means that researchers must find appropriate embedding for virtual clusters in DCNs. This section provides a brief overview of the relevant methodologies proposed to address this problem. Since most research focuses on dynamically adjusting cluster size without considering bandwidth guarantees targeted by current network abstractions, several methods have been proposed. [6] proposes scaling a virtual network abstraction with a bandwidth guarantee. Efficient algorithms are proposed to find a valid allocation for the scaled cluster abstraction with optimization on the VM locality of the cluster. [7] proposes a virtual cluster abstraction called Stochastic Virtual Cluster (SVC) to realize bandwidth guarantee during the resource allocation. The framework and algorithms ensure that the bandwidth demands of tenants on a link are satisfied with a high probability while minimizing the bandwidth occupancy cost on links.

Elasticity has been considered one of the central attributes of cloud computing [8]. In cloud computing, elasticity is defined as the degree to which a system is able to adapt to workload changes by provisioning and de-provisioning resources in an autonomic manner [9]. In order to define a measure of the elasticity, [10] provides a set of benchmarks for cloud computing performance. Elastic resource scaling has attracted considerable attention in cloud computing [5], [11]. [12] proposes a lightweight approach to enable cost-effective elasticity for cloud applications; this is realized by designing an automatic system. There are also a number of works about scaling resources using a prediction-driven method. [13]–[15] employ resource demand prediction to achieve elastic resource allocation without assuming prior knowledge of the applications in the cloud. [15] is slightly different, as it uses VM replication to reduce application start-up times.

A few works consider coordinated VC scaling on both optimization of the VCs' localities and the elastic resource allocation. [16] proposes a system that allows tenants to dynamically request and update minimum guarantees for both network bandwidths and compute resources at runtime; this is realized using the resource reservation method. [17] studies survivable and bandwidth-guaranteed embedding of virtual clusters, and it proposes a novel algorithm to jointly optimize primary and backup embeddings of the virtual clusters. These works on VC resource allocation fail to fully consider both localities and elasticities for the scaling requests in one determined time period. In this paper, we jointly consider VC placement on localities and elasticities with scaling fluctuation to maximize the over-time elasticity during one time period with minimal extra cost in DCNs.

III. MODEL AND PROBLEM FORMULATION

A. PLATFORM MODEL

This paper focuses on the elastic VC scaling placement problem for the hose communication model in fat-tree. We jointly consider localities and elasticities during resource allocation for VC scaling, and we use elasticity to measure the growth potential for VCs, an important factor for weighting flexibility during the placement. Our objective is to maximize the elasticity for VCs with a communication cost constraint in the DCN.

B. DATA CENTER MODEL

In this paper, we consider the fat-tree as our data center network topology model. Fat-tree is an extended tree topology which has been applied to DCNs by several researchers [18]. In fat-tree, each θ-port switch in the edge layer is connected to $\frac{\theta}{2}$ PMs [18]. Each PM in the fat-tree is denoted as M_i and divided into multiple slots where VMs can be placed. The capacity of each PM is denoted by C_i, and the PMs in the DCN are homogeneous. The PLs are denoted by $L = \{L_{ij}\}$, and the capacity of PL is denoted by B_{ij}. $T_{S_{ij}}$ denotes the subtree under the root (physical switch) S_{ij} that contains a set of PMs and PLs. In this paper, we set the root (physical switch) S_{ij} as the $locality$, which we use to denote the position of the virtual cluster V_i. There are two properties of the $locality$, private and public. When the property is private, the resource of the subtree $T_{S_{ij}}$ can only be used by V_i. Otherwise, the resource under the subtree $T_{S'_{ij}}$ can be used by any VC.

C. VIRTUAL CLUSTER (VC)

The VC is an abstraction that allows each tenant to specify both the virtual machines (VMs) and per-VM bandwidth demand of its service [19]. Let V_i denote the i^{th} existing VC in the DCN. Each VC consists of a set of VMs and one virtual switch where $V_i =< N_i, B_i >$. N_i is the number of VMs in the i^{th} VC, and B_i is the bandwidth demand between VMs and the virtual switch. In this paper, we consider the hose model based on the VC abstraction. In the hose model, each customer specifies a set of endpoints to be connected with a common endpoint-to-endpoint performance guarantee [20].

1) Communication Cost

Since a good locality means that the allocation of a virtual cluster to reduce the communication latency among VMs, we define a new function can measure communication cost. The standard metric to evaluate communication cost is measuring the embedded footprint [1], [21], [22]. During the VM placement, we try to minimize the communication cost. For each virtual request V_i,

$$m(V_i) := \sum_{j=1}^{3} \left|T_{S_{ij}}\right| \cdot H_j \cdot \gamma \tag{1}$$

$\left|T_{S_{ij}}\right|$ denotes the total amount of VMs under the subtree L_{ij} of virtual cluster V_i, as shown in equation (1). H_j is the hops between PMs holding the VMs of V_i. Since the architecture of the DCN is fat-tree in this paper, the value of H_j is $H_1 = 2$, $H_2 = 4$, $H_3 = 6$. γ is a constant value which denotes the communication cost between each pair of VMs in V_i. The communication cost of a virtual request can be calculated via the following case distinction: (1). If all VMs of V_i place into one PM, the communication cost $m(V_i) = 0$. (2). If V_i places under the ToR switches or aggregation switches of a pod, the communication cost $m(V_i) = 2 * \left|S_{L^0_{i1}}\right| + 4 * \left|S_{L^1_{i1}}\right|$. (3). If V_i places under the core switches of different pods, the communication cost $m(V_i) = 6 * |S_{L_{i3}}|$.

2) Elasticity

Let E_i denote the elasticity of V_i, which measures the growth potential of V_i under the communication cost constraint. In this paper, we use this factor to weigh the flexibility of the placement of the VCs.

TABLE 1. Notations

Symbol	Description
M_i	PM in the DCN
C_i	Capacity of the i^{th} PM in the DCN
L_{ij}	PL in the DCN
B_{ij}	Capacity of PL in the DCN
V_i	The i^{th} existing VC in the DCN
N_i	Existing VMs of V_i
N'_i	Scaling VMs of V_i
B_i	Existing bandwidth demand of V_i
δB_i	Scaling bandwidth demand of V_i
$T_{S_{ij}}$	Subtree of V_i under the locality (root) S_{ij}
$R^M_{S_{ij}}$	Available computing resource in the subtree $T_{S_{ij}}$ for V_i
$R^L_{S_{ij}}$	Available communication resource in the subtree $T_{S_{ij}}$ for V_i
$m(\cdot)$	Communication cost of V_i
Φ	Upper bound for communication cost
ρ_i	Scaling ratio for V_i
ζ_i	Adjust factor of the elasticity for V_i

Definition 1: **Combinational elasticity** is defined as $E_i = \min\{E^M_i, E^L_i\}$, where E^M_i is defined as the minimum percentage of available VM slots among PMs under the subtree $T_{S_{ij}}$ of V_i.

$$E^M_i = \min_{C_i \in T_{S_{ij}}} \{1 - \max_i \frac{C^*_i + C'_i}{C_i}\} \tag{2}$$

Similarly, E^L_i is defined as the minimum percentage of available communication resource (bandwidth) among PLs under the subtree $T_{S_{ij}}$ of V_i, in equation (3).

$$E^L_i = 1 - \max_{ij} \frac{f(\sum_{C_i \in T_{S_{ij}}} (C^*_i + C'_i))}{B_{ij}} \tag{3}$$

C^*_i and C'_i denote the number of existing and incoming VMs of V_i belong to the PMs under the subtree $T_{S_{ij}}$. Similarly, $f(\sum_{C_i \in T_{S_{ij}}} (C^*_i + C'_i))$ denotes the communication demand under the subtree $T_{S_{ij}}$, where $f(\cdot)$ denotes the bandwidth demand function of VM communications.

D. BASIC PROBLEM FORMULATION

1) Definition of VC Scaling Placement

In this paper, we consider the VC placement based on the hose model and fat-tree. Let $V_i =< N_i, B_i >$ denote the i^{th} VC, which contains several types of problem instances for scaling up. The basic ones are either to increase the cluster size on the computing resource from N_i to $N_i + N_i$ or to increase the communication resource from B_i to δB_i. The most difficult is to increase both computation and communication resources, which range from N_i to $N_i + N_i$ and from B_i to δB_i, i.e., $V_i =< N_i, B_i >$ or $V_i =< N_i + N'_i, \delta B_i >$. We mainly focus on the latter case, combined resource scaling , and the algorithms we propose for it can also efficiently solve the other two types of scaling problems.

2) Objective Function

Our objective is to maximize the elasticity of V_i with the constraint of communication cost. We use a constant Φ to denote the upper bound of the communication cost that is initialized by the users based on the demands of the applications [21]. Our problem can be formally formulated as follows:

$$\text{maximize } E_i \tag{4}$$

$$\text{subject to } 0 \leq m(V_i) \leq \Phi_i \tag{5}$$

$$C_i^* + C_i' \leq C_i \tag{6}$$

$$f(\sum_{C_i \in T_{S_{ij}}} (C_i^* + C_i')) \leq B_{ij} \tag{7}$$

Variables are C_i' and B_{ij}', and E_i is derived. Others are given, i.e., C_i^*, B_{ij}^*, and Φ_i. Equation (5) shows the constraints on the communication cost $m(V_i)$ where the value should be greater than or equal to 0 with the upper bound Φ_i. Equation (6) shows the constraints on capacities of PMs, in which the total number of existing and incoming VMs C^* and C_i' on the i^{th} PM cannot exceed the capacity C_i. Equation (5) is the link capacity constraint, which shows that the bandwidth usage of both the existing and incoming VMs on L_{ij} under the subtree $T_{S_{ij}}$ can not exceed the link capacity B_{ij}. The major notations used in this paper are listed in Table I.

IV. SINGLE VIRTUAL CLUSTER SCALING

This section proposes one optimal solution, VCS, that can be applied to deal with the scaling of a single virtual cluster.

A. ALGORITHM AND DESCRIPTION

1) Initialization

We take the incoming scaling request for V_i with $\langle N', \delta B \rangle$ at time slot t_i as the input, and the output is the occupation state for V_i in the DCN. The initialization in line 1 is to find the locality S_{ij} of V_i and calculate the available physical resource under the subtree $T_{S_{ij}}$. The available resource contains both computation resource $R_{S_{ij}}^M = \sum_{M_i \in T_{S_{ij}}} C_i'$ and communication resource $R_{S_{ij}}^L = \sum_{L_{ij} \in T_{S_{ij}}} B_{ij}'$. We also initialize the upper bound of the communication cost Φ_i for V_i, which users usually set as the QoS guarantee.

2) Virtual Cluster Scaling (VCS)

For each scaling request, we try to find the appropriate subtree to obtain enough physical resources. In lines 2 and 3, we first compare the incoming scaling request $\langle N', \delta B \rangle$ with the total available physical resource, $R_{S_{ij}}^M$ and $R_{S_{ij}}^L$, under $T_{S_{ij}}$. If the total amount of available physical resource cannot satisfy the scaling request, the current subtree root will be positively adjusted by the step $T_{S_{ij}}$=$T_{S_{L_{i,j+1}}}$ in line 5. This process ends when the locality moves to the upper bound S_{ij}'. We start to place scaling requests in line 6 using the function $VMP(N', \delta B)$, which is described in Algorithm 2.

3) VM Placement (VMP)

In this section, we propose an efficient algorithm to find a valid allocation for the scaled virtual cluster with optimization of the VMs' localities. The initialization in line 1 calculates the partial elasticity under the subtree $T_{S_{ij}}$, which is denoted as $E_{T_{S_{ij}}}$. To adjust the partial elasticity under $T_{S_{ij}}$, we define a factor ζ_i. Before allocating the computation resource, we check the scaling condition of the communication resource in line 2, which can ensure that the bandwidth B_i for each VM appropriately reserves communication resource on physical links. If δ is not equal to 1, the communication resource has to scale or release, and we update the bandwidth capacities for the existing VMs of V_i under the communication demand δB_i in line 3. Otherwise, the communication resource does not have any scaling or releasing. After that, we compute the available computation and communication capacities under the subtree $T_{S_{ij}}$ with the limitation of $E_{T_{S_{ij}}}$ in line 4. From lines 5 to line 9, we start to allocate computation resource under the subtree $T_{S_{ij}}$, and we place N_i' VMs into PMs based proportionally on the remaining available capacities. If the total number of available physical resources cannot satisfy the scaling request, the current partial elasticity is negatively adjusted by the step factor ζ, as shown in lines 8 and 9. This process ends when the partial elasticity $E_{T_{S_{ij}}}$ is 0. In line 10, the communication demands of the placed VMs are evenly split into paths that connect them under the subtree $T_{S_{ij}}$.

Algorithm 1 Virtual Cluster Scaling (VCS)

Input: Scaling request V_i with $\langle N_i', \delta B_i \rangle$;
Output: DCN occupation state for V_i;

1: Initialize the initial locality S_{ij} and communication cost Φ_i for V_i, and calculate the available physical resources under the subtree $T_{S_{ij}}$;
2: Calculate the highest locality S_{ij}' based on the communication cost Φ_i;
3: **for** S_{ij} to S_{ij}' **do**
4:   **while** $R_{S_{ij}}^M < N_i' \vee R_{S_{ij}}^L < N_i^* * \delta B_i$ **do**
5:     $T_{S_{ij}}$=$T_{S_{L_{i,j+1}}}$;
6:   **end while**
7:   $T_{S_{ij}} \leftarrow VMP(N_i', \delta B_i)$;
8: **end for**

B. OPTIMALITY ANALYSIS

Theorem 1: VCS is an optimal solution for the V_i placement under the communication cost constraint Φ.

Proof: The maximum number of servers in a fat-tree is $\frac{\theta^3}{4}$. We start to prove from $\theta = 2$, which contains 2 PMs in fat-tree. For the virtual cluster V_i, we suppose that VCS is not an optimal solution, meaning that another solution O will be the optimal one. Since the bandwidth resource is not oversubscribed, the bottleneck of the elasticity exists on the computation resource. Let $\hat{C}_a$ and $\hat{C}_b$ denote the remaining available slots of PMs a and b under the subtree $T_{S_{ij}}$ of V_i. In order to place the scaling N' VMs, we assume the optimal solution O is $\{x, y\}$ $(x + y = N')$, where x VMs are placed on a and y VMs are placed on b. Similarly, we suppose the solution calculated by VCS is $\{u, v\}$ $(u + v = N')$, where u VMs are placed on a and v VMs are placed on b. We suppose

Algorithm 2 VM Placement (VMP)

Input: Scaling request V_i with $\langle N_i', \delta B_i \rangle$;
Output: DCN occupation state for V_i;

1: Initialize E_i and adjust factor ζ_i for V_i;
2: **if** $\delta \neq 1$ **then**
3:   Update the capacities of PLs for existing VMs of V_i according to the scaling $B_i \to \delta B_i$;
4: **end if**
5: Compute $R_{L_{ij}}'^{M}$ and $R_{L_{ij}}'^{L}$ according to E_i under $T_{S_{ij}}$;
6: **while** $E_i > 0$ **do**
7:   **if** $N_i' \leq R_{L_{ij}}'^{M}$ **then**
8:     Place N_i' VMs into PMs in $T_{S_{ij}}$ (proportion based on the remaining available capacities of PMs);
9:   **else if** $N_i' > R_{L_{ij}}'^{M}$ **then**
10:     Update $E_i = E_i - \zeta_i$;
11:   **end if**
12: **end while**
13: Communication demands of placed VMs are evenly split into paths connecting them;

$x > u$, and we have $y < v$. The elasticity of V_i under the optimal solution O is $\min\{\frac{\hat{C_a}-x}{C}, \frac{\hat{C_b}-y}{C}\}$ if $x > y$. Then, the value of the elasticity is $\frac{\hat{C_a}-x}{C}$. If the elasticity under the VCS solution is $\frac{\hat{C_a}-u}{C}$, $\frac{\hat{C_a}-x}{C} > \frac{\hat{C_a}-u}{C}$. However, we have $x < u$, which obeys our assumption that $x > u$. Therefore, we can prove that VCS is an optimal solution when $\theta = 2$. We further assume that VCS is optimal when $\theta = k$, and we prove that it is also optimal when $\theta = k+2$. Each $k+2$ port switch in the edge layer is connected to $\frac{k+2}{2}$ PMs. We assume that vector X is the optimal solution and that $X = \{x_1, x_2, ..., x_{\frac{k}{2}}, x_{\frac{k}{2}+1}\}$. The placement of the items is different than VCS. Since X is the optimal solution, each part in its set is optimal; this is contrary to the assumption that VCS is optimal when $\theta = k$. Therefore, we can prove that VCS is an optimal solution for the V_i placement under the communication cost constraint Φ. ■

V. MULTIPLE VIRTUAL CLUSTER SCALING

In this section, we extend our work to the multiple VC scaling problem. We assume that a set of VCs V already exists in the DCN, and each VC uses the notation V_i to denote where $V = \{V_1, V_2, ..., V_\varpi\}$. Multiple VCs may request to scale at the same time, but each time slot can only deal with one VC scaling request. We consider the performance of VCs in the time period $[0, T]$ using over-time elasticity.

A. DESCRIPTION

Definition 2: Let the amount of the VCs be ϖ; **over-time elasticity** is the summation of the combinational elasticities of V_i under the time slots during the whole time period $[0, T]$, i.e., $\sum_{i=0}^{T} E_i$.

For offline multiple virtual cluster scaling, since the initial distributions of the VCs are different, the processing order for the multiple ϖ VCs may lead to different results. Take Fig. 3 for example; three VCs exist in the DCN, and the numbers of existing VMs for these users are 5, 2, and 7, respectively. The communication costs for the three VCs have already changed into the position of subtree root, which is marked by cycles with different corresponding colors in Fig. 3. When all three VCs send their scaling requests, we schedule them in the order VC1→VC2→VC3, as shown in Fig. 3 (a). Then, we have the elasticities VC1=$\frac{1}{5}$, VC2=$\frac{1}{5}$, and VC3=$\frac{1}{5}$, respectively. The over-time elasticity for all three VCs is $\frac{1}{5}+\frac{1}{5}+\frac{1}{5} = \frac{3}{5}$. When we change the scheduling order to VC2→VC3→VC1, as shown in Fig. 3 (b), the elasticities are VC1=$\frac{1}{5}$, VC2=$\frac{1}{5}$, and VC3=$\frac{2}{5}$, respectively. The over-time elasticity for all three VCs under this scheduling strategy is $\frac{1}{5}+\frac{1}{5}+\frac{2}{5} = \frac{4}{5}$.

Theorem 2: The MVCS placement for the over-time elasticity maximization problem is NP-hard.

Proof: Given a set of scaling VCs, $V = \{V_1, V_2, ..., V_\varpi\}$. Let the amount of existing VCs be ϖ, and they request to scale at the same time t. We assume the rest of the available resource of the DCN at t is R. The communication cost of each VC is related to the locality of its placement, which has a limitation Φ defined by the uses. The goal is to place all ϖ VCs using the fewest physical resources with determined capacities under the communication cost Φ. We reduce the original problem to the variable-sized bin-packing problem [22], [23], an NP-hard problem that finds an assignment that uses the fewest bins. Thus, the MVCS placement for the over-time elasticity maximization problem is NP-hard. ■

Before describing the algorithm, we first introduce an important parameter scaling ratio.

Definition 3: Let ρ_i denote the scaling ratio of the virtual cluster i, which is the ratio between the scaling amount of V_i and the maximum available physical resource $R_{S_{ij}}$ under the subtree $T_{S_{ij}}$.

$$\rho_i = \frac{V_i}{R_{S_{ij}}} \tag{8}$$

We use ρ_i measure the scaling level of the virtual cluster V_i. Since the physical resource $R_{S_{ij}}$ for V_i is limited by the communication cost Φ_i, the scaling amount of V_i should be under the constraint in Equation (8). Therefore, the range of the scaling ratio is $0 < \rho_i < 1$.

B. ALGORITHM

Since MVCS placement is an NP-complete problem, we propose a heuristic algorithm to find a consistent scaling scheduling order that improves the over-time elasticity as much as possible. We take the incoming scaling request set $V = \{V_1, V_2, ..., V_\varpi\}$ as the input, and the output is the occupation state for V in the DCN.

The initialization in line 1 finds the localities S_{ij} for VCs and calculates the available physical resource under the subtree $T_{S_{ij}}$. Based on that, we initialize the scaling ratio ρ_i, which is the ratio between the scaling amount of V_i and the available physical resource under the subtree $T_{S_{ij}}$, i.e.

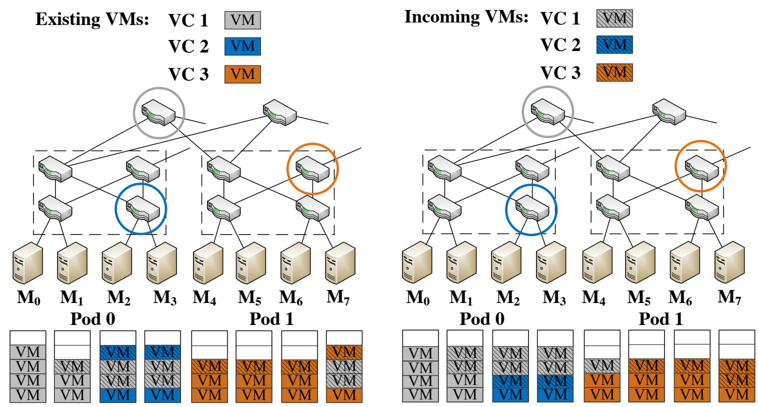

FIGURE 3. An example of different placements for the scaling of multiple VCs.

Algorithm 3 Multiple Virtual Cluster Scaling (MVCS)

Input: Scaling set $V = \{V_1, V_2, ..., V_\varpi\}$;
Output: DCN occupation state for V;

1: Initialize the localities S_{ij} and S'_{ij}, ρ_i and Φ_i for VCs;
2: Sort VCs in the set V to V' by localities $i = \arg\min_i S'_{ij}$;
3: For VCs with the same localities, prioritize by scaling ratio $i = \arg\min_i \rho_i$;
4: **for** $i = 1$ to $i = \varpi$ in V' **do**
5: Place V_i into the DCN;
6: Same as Algorithm 1 form line 2 to line 5;
7: **end for**

$0 < \rho_i < 1$. After that, we initialize the upper bound of the root position S'_{ij} based on the communication cost Φ_i for VCs in the set V. In line 2, we first sort VCs in the set V to V' by localities $i = \arg\min_i S'_{ij}$ based on the communication cost Φ_i. Let V' be the sorting result of the scaling VCs. If the level of S'_{ij} is the same for the VCs, let the lower scaling ratio ρ_i have higher priority in line 3. From lines 4 to 6, we start to place the VCs in the DCN by prioritizing the VCs in the set V' with the lower localities and scaling ratios ρ_i. The placement process for each VC is the same as in Algorithm 1, line 6.

VI. ONLINE MULTIPLE VIRTUAL CLUSTER SCALING

In this section, we describe the online condition for the multiple VC scaling problem with synchronous and asynchronous incoming rates.

A. SYNCHRONOUS ONLINE MULTIPLE VIRTUAL CLUSTER SCALING (S-OMVCS)

In this section, we address the online multiple virtual cluster scaling problem with a synchronous incoming rate. The scaling requests of virtual clusters in set V are incoming at the same time slot and also release at the same time slot. Multiple VCs can make scaling requests simultaneously, but a single time slot can only deal with one VC scaling request. We consider the performance of VCs in a single time period $[0, T]$ using over-time elasticity. For each virtual cluster, the incoming scaling amount is uncertain, and we need to preprocess existing virtual clusters, including priority ranking and future prediction. The future prediction is based on the Bayesian parameter estimation, as discussed below. Let ρ_i^* denote the maximum scaling ratio for the virtual cluster V_i, which means that the flexibility of resources under the subtree S'_{ij} should not beyond the communication cost Φ_i. The priority ranking for multiple scaling requests is the same as in offline requests, which depend on both the upper bound of the root position S'_{ij} and the scaling ratio ρ_i.

1) Bayesian Parameter Estimation for S-OMVCS

Based on the current incoming scaling V_i request, we use Bayesian parameter estimation [24] to predict the future fluctuation statement for each virtual cluster. We use the historical fluctuation statement before T_n as our sample, denoted as $\mathbb{I} = \{N'_i|_{i\in[0,T_n]}\}$. Let n denote the number of samples in $\mathbb{I}$, which means that the current location is at the $n+1$ time slot. As we move through the time slots, the new observation samples are obtained, and the posterior probability density function is sharpened to form the largest spike near the true value of the parameter. We use Bayesian parameter estimation based on uniform distribution to predict the future information of the scaling virtual cluster V_i, and each virtual cluster is independent and identically distributed. We use the standard Gaussian distribution as the prior distribution, i.e., $\mu_0 = 0$ and $\delta_0^2 = 1$; this is the same as in [26]. Before doing the prediction, we first calculate the maximum likelihood μ' for the sample $\mathbb{I}$, where $\mu' = \frac{1}{n}\sum_{i=1}^{n} N'_i$. According to the prior and maximum likelihood values, we have the posterior distributions $\mu = \frac{n}{n+\delta^2}\mu'$ and $\delta^2 = \frac{\delta'^2}{n+\delta'^2}$. Based on the Bayesian estimation, we have the probability

Algorithm 4 Synchronize Online Multiple Virtual Cluster Scaling (S-OMVCS)

Input: Scaling set $V = \{V_1, V_2, ..., V_\varpi\}$ at time slot t_i;
Output: DCN occupation state for V;

1: Initialize the localities S_{ij} and S'_{ij}, ρ_i and Φ_i for VCs;
2: **for** $i = 1$ to $i = \varpi$ in V **do**
3: Estimate the fluctuating mean μ_i for V_i based on bayesian parameter estimation;
4: Calculate the future scaling ratio ρ_i^* based on the μ_i;
5: Relocate the locality property S_{ij}^* based on the ρ_i^*;
6: Make resource reservations according to S_{ij}^* for V_i;
7: **end for**
8: Sort VCs in the set V to V' by localities $i = \arg\min_i S_{ij}^{'*}$;
9: **for** $i = 1$ to $i = \varpi$ in V' **do**
10: For VCs with the same localities, prioritize by scaling ratio $i = \arg\min_i \rho_i^*$;
11: Place the scaling request V_i into the DCN;
12: Same as Algorithm 1 form line 2 to line 8;
13: **end for**

density function in Equation (9).

$$p(\mu_i|\mathbb{I}) = \frac{1}{(\sqrt{2\pi})\delta} \exp\left[-\frac{1}{2\delta^2}\sum_{i=1}^{n}(\mu_i - \mu)^2\right] \tag{9}$$

2) Algorithm and Description

We take the set of scaling requests V arriving at time slot t_i as the input, and the output is the occupation state for V in the DCN. Since the scaling requests of the virtual clusters in set V are synchronously incoming, we use the same initialization as MVCS (**Algorithm 3**, in line 1). In lines 2 to 7, we start to estimate the future information for the incoming virtual clusters. For each virtual cluster, we first estimate the fluctuating amount of μ_i and δ for V_i based on Bayesian parameter estimation. Then, we calculate the future scaling ratio ρ_i^* based on the μ_i, and we relocate the locality property S_{ij}^* based on the ρ_i^*. We use S_{ij}^* for resource reservation for V_i. In line 8, we sort VCs in the set V to V' by localities $i = \arg\min_i S_{ij}^{'*}$ and start to deploy each VC in V'. From lines 9 to 13, we start to deploy each VC in V one-by-one based on the sorting order. VCs with the same localities are prioritized by the scaling ratio $i = \arg\min_i \rho_i^*$. In line 11, we start to place the V_i into the DCN, and the placement process for each V_i is the same as **Algorithm 1** from lines 2 to 8.

B. ASYNCHRONOUS ONLINE MULTIPLE VIRTUAL CLUSTER SCALING (A-OMVCS)

In this section, we address the online multiple virtual cluster scaling problem with an asynchronous incoming rate. In this condition, the scaling requests of virtual clusters in set V are incoming at different time slots and also release at different time slots. For each time slot, the incoming scaling amount of virtual clusters is uncertain. Let the fluctuation of incoming numbers of the VCs with Gaussian distribution be $N(\hat{\mu}, \hat{\delta}^2)$. Since the scaling amount of the VCs is uncertain at each time slot, if we use the same reservation scheme in **Algorithm 4**, resource utilization will be inefficient. Therefore, we need to predict not only the scaling information for each virtual cluster, but also the incoming amount of virtual clusters at the next time slot. We preprocess each currently existing virtual cluster in the same way as in the synchronous case. In the asynchronous case, multiple VCs can make scaling requests together at the same time slot, but each time slot can only deal with one VC scaling request. We also consider the performance of VCs in a single time period $[0, T]$ using over-time elasticity.

1) Bayesian Parameter Estimation for A-OMVCS

In the asynchronous online scaling case, we first do the prediction for the incoming scaling VCs. We use Bayesian parameter estimation to predict the future fluctuation statement for virtual clusters. Let κ_i denote the incoming VCs at time slot t_i; we use the historical fluctuation statement $\mathbb{Z} = \{\kappa_i|_{i\in[0,T_n]}\}$ of VCs before T_n as our sample. Let n denote the number of samples in $\mathbb{Z}$, which means the current location is at the $n+1$ time slot. We use the standard Gaussian distribution as the prior distribution, i.e., $\hat{\mu}_0 = 0$ and $\hat{\delta}_0^2 = 1$. Then, we calculate the maximum likelihood $\hat{\mu}'$ for the sample $\mathbb{Z}$, where $\hat{\mu}' = \frac{1}{n}\sum_{i=1}^{n}\kappa_i$. According to the prior and maximum likelihood values, we have posterior distributions where $\hat{\mu} = \frac{n}{n+\hat{\delta}^2}\hat{\mu}'$ and $\hat{\delta}^2 = \frac{\hat{\delta}'^2}{n+\hat{\delta}'^2}\hat{\mu}'$. Based on the Bayesian estimation, we have the probability density function in Equation (10).

$$p(\hat{\mu}_i|\mathbb{Z}) = \frac{1}{(\sqrt{2\pi})\hat{\delta}} \exp\left[-\frac{1}{2\hat{\delta}^2}\sum_{i=1}^{n}(\hat{\mu}_i - \hat{\mu})^2\right] \tag{10}$$

2) Algorithm and Description

We use the same input and output settings as **Algorithm 5**, which includes κ_i VCs at time slot t_i. In line 1, we do the same initialization as MVCS (**Algorithm 3**). Then, we estimate the fluctuating mean $\hat{\mu}_i$ for incoming VCs based on Bayesian parameter estimation in line 2. According to the mean $\hat{\mu}_i$, we calculate the scaling amount $\hat{\kappa}_i$ of VCs in line 3. In lines 4 to 7, we start to estimate future information for each of the incoming virtual clusters, and we sort VCs in the set V to V' by localities $i = \arg\min_i S_{ij}^{'*}$. In lines 8 to 10, we make resource reservations for the $\hat{\kappa}$ VCs in the set V' that has the highest probability for scaling requests in the incoming time slots. In lines 11 to 13, we start to place the κ VCs into the DCN, and the placement process is the same as in **Algorithm 4** from lines 9 to 13.

VII. EXPERIMENTS

This section conducts extensive simulations to study elastic VC scaling placement under three aspects: single VC scaling, multiple VC scaling, and online multiple VC scaling. These experiments are conducted to evaluate the performances of the proposed algorithms. After presenting the datasets and

Algorithm 5 Asynchronous Online Multiple Virtual Cluster Scaling (A-OMVCS)

Input: Scaling set $V = \{V_1, V_2, ..., V_{\kappa_i}\}$ at time slot t_i;
Output: DCN occupation state for V;

Initialize the localities S_{ij} and S'_{ij}, ρ_i and Φ_i for VCs at time slot t_i;
Estimate the fluctuating mean $\hat{\mu_i}$ for incoming VCs based on Bayesian parameter estimation;
Calculate the scaling amount $\hat{\kappa_i}$ of VCs based on the $\hat{\mu_i}$;
for $i = 1$ to $i = \kappa$ in V **do**
  Same as Algorithm 4 from line 3 to line 5;
end for
Sort VCs in the set V to V' by localities $i = \arg\min_i S'^{*}_{ij}$;
for $i = 1$ to $i = \hat{\kappa_i}$ in V' **do**
  Make resource reservations according to S^*_{ij} for V_i;
end for
for $i = 1$ to $i = i = \kappa$ in V' **do**
  Same as Algorithm 4 form line 9 to line 13;
end for

settings, the results are shown from different perspectives to provide insightful conclusions.

A. SINGLE VIRTUAL CLUSTER SCALING

1) Experiment Setting

The DCN is modeled as a fat-tree, in which the number of switches' ports are $\theta = 4$, $\theta = 6$, and $\theta = 8$. Let the amount of PMs in the fat-tree be fully connected with the maximum numbers, which are 16, 54, and 128, respectively. The supplied computing and communication resources of the PMs and PLs are real numbers uniformly distributed between 50 and 100 units. For each group with a different switch's port, we calculate elasticity after the scaling placement process. The results are averaged 10 times for each algorithm. We compare the proposed VCS algorithm with the two benchmark algorithms in a number of trace-driven settings.

- Equally Scaling (ES): the scaling request of V_i is evenly divided into several pieces depending on the amount of PMs in the sub-tree. It can obtain the load-balance for each virtual request [1].
- Greedy Scaling (GS): the scaling request of V_i for the PMs depends on the amount of available resource in the sub-tree; PMs with high margins have a high priority.

2) Experiment Results

Fig. 4, Fig. 5, and Fig. 6 present the elasticity for the single VC scaling condition, in which the numbers of the switches' ports are $\theta = 4$, $\theta = 6$, and $\theta = 8$, respectively. For each group experiment, we use the same three algorithms: ES, GS, and VCS, and we calculate averaged 10 times of the elasticities for various scaling requests. Additionally, we have the following observations: (i). The elasticity of the scaling

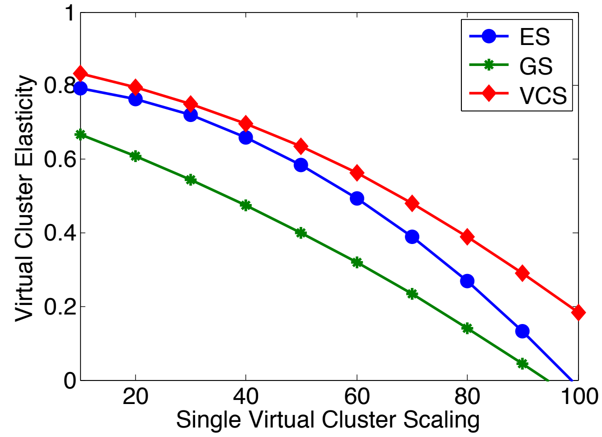

FIGURE 4. The elasticity for single VC scaling under various fat-trees ($\theta = 4$).

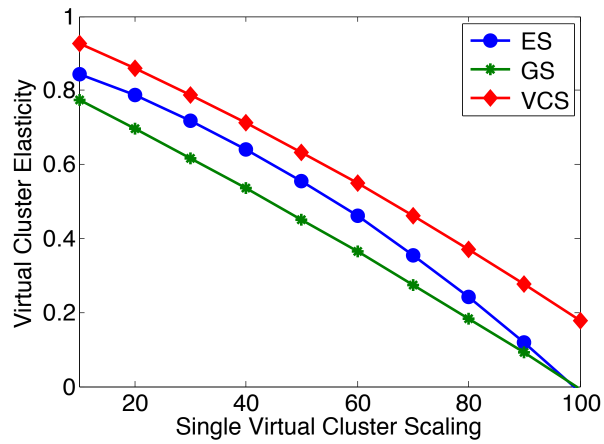

FIGURE 5. The elasticity for single VC scaling under various fat-trees ($\theta = 6$).

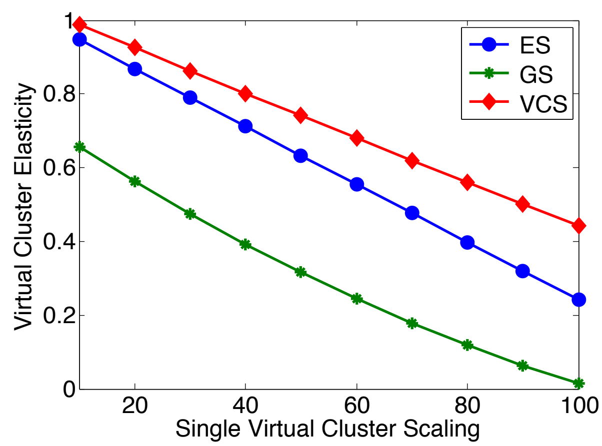

FIGURE 6. The elasticity for single VC scaling under various fat-trees ($\theta = 8$).

VC depends on the architecture of the fat-tree. Since the construction of DCNs is based on the number of switches' ports, we can see that the elasticity of the VC with scaling

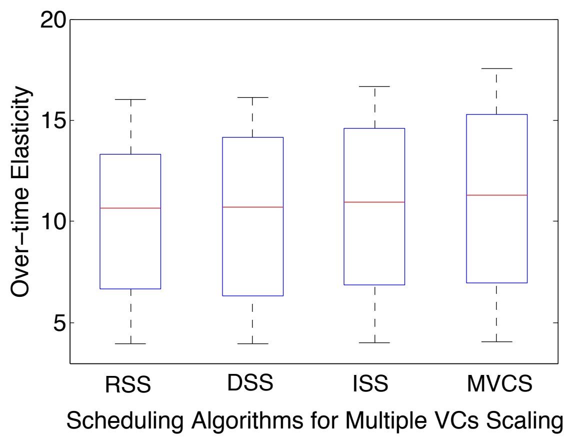

FIGURE 7. The elasticity for the scaling of multiple VCs.

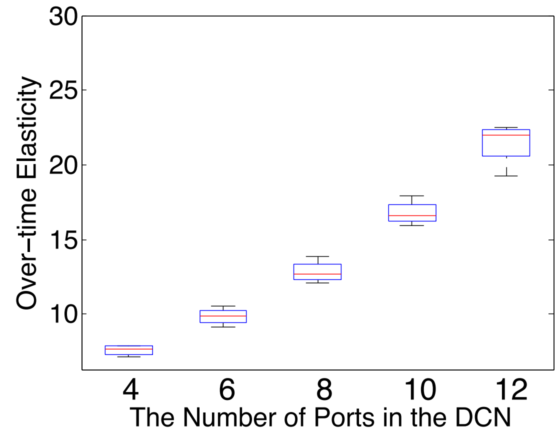

FIGURE 8. The over-time elasticity for S-OMVCS (online without prediction).

under the $\theta = 4$ switch is much lower than that of the fat-trees where $\theta = 6$ and $\theta = 8$. (ii). The elasticity of the scaling VC depends on various placement algorithms. As shown in Fig. 4, Fig. 5, and Fig. 6, the performance of GS decreases significantly with the increase in the scaling of VC. ES's performance depends on the existing localities of the existing VMs. Therefore, the fluctuation of FFRP is much larger in ES than in other algorithms. Compared with ES and GS, VCS has the best performance in elasticity.

B. MULTIPLE VIRTUAL CLUSTER SCALING

1) Experiment Setting

This section evaluates the elasticity of the scaling of multiple VCs scaling and uses the same data set as the single VC scaling problem. Set the VMs of the VCs scaled at one time slot are evenly distributed between 0 and 50, the bandwidth demands δ scale between 0 and 1. Let the switch's port be $\theta = 4$, $\theta = 6$, and $\theta = 8$ for each group. In addition to the proposed algorithms, three baseline algorithms are used:

- Random Schedule Scaling (RSS): the scheduling order for the multiple VCs is random.
- Decreasing Schedule Scaling (DSS): the scheduling order for the multiple VCs is decreasing.
- Increasing Schedule Scaling (ISS): the scheduling order for the multiple VCs is increasing.

2) Experiment Results

Since the scale of the VMs ranges from 0 to 50, we calculate the even value of the over-time elasticity under different δ between 0 and 1. We use the over-time elasticity to evaluate the performance of the proposed algorithm, and we compare it with three base-line algorithms: RSS, DSS, and ISS. Fig. 7 presents the over-time elasticity of the scaling of multiple VCs using different schedule strategies. The number of scaling VCs at the time slot is evenly distributed from 0 to 50. For each time slot, we allow one VC to be processed. According to the simulation results, we have the following observations: (i). The volatility of the multiple scaling VCs is stable. As

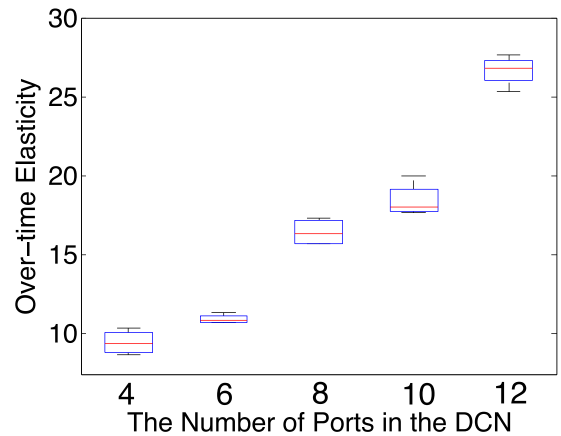

FIGURE 9. The over-time elasticity for S-OMVCS (online with prediction).

shown in Fig. 7, the mean values are marked by red lines, which are close to each other under different algorithms. (ii). The over-time elasticity for the multiple VCs depends on the scheduling order. Comparing these four algorithms, the performance of RSS is the worst. The interval range of ISS is better than that of DSS, which depends on the distribution of existing VMs of the VCs. Compared with RSS, DSS, and ISS, MVCS has the best performance in over-time elasticity.

C. ONLINE MULTIPLE VIRTUAL CLUSTER SCALING

1) Experiment Setting

This section evaluates the elasticity of online multiple VC scaling, in which the arrival times of VCs are discretionary and scaling amounts are randomly determined by tenants. We divide the scaling into two parts: synchronous online multiple VC scaling and asynchronous online multiple VC scaling. We set the scaling frequency of the VCs to 1, which means that each time slot has to process the scaling or releasing requests. We run each of our simulations for 10 time slot intervals. The parameters and symbols that we vary in our simulations are over-time elasticity.

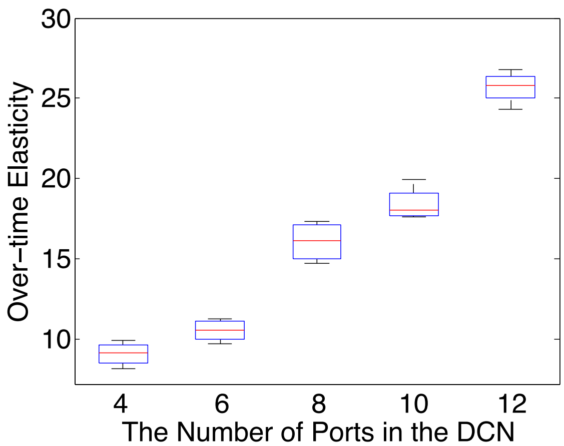

FIGURE 10. The over-time elasticity for A-OMVCS.

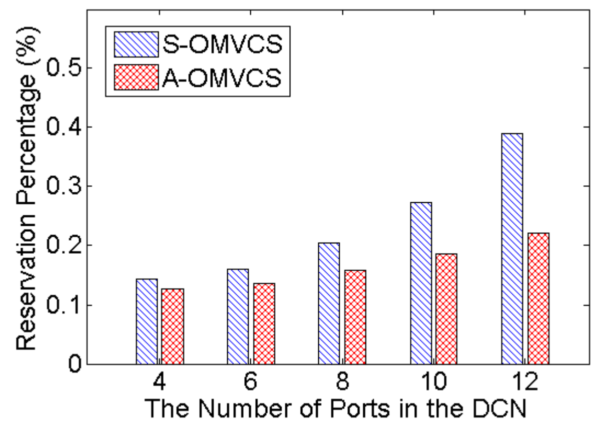

FIGURE 11. The resource reservation for S-OMVCS and A-OMVCS.

2) Experiment Results

Since incoming scaling VCs are online, the placement for VCs at the current time slot is important to incoming VCs in future time slots. We compare our S-OMVCS algorithm with the algorithm without prediction. Fig. 8 and Fig. 9 present a comparison of performances for the two solutions by calculating the over-time elasticity under different distributions of existing VCs with various capacities ($\theta = 4$, $\theta = 6$, $\theta = 8$, $\theta = 10$, and $\theta = 12$). For the online scaling, the uncertainty of scaling VCs (in both size and number) leads to various interval sizes of the elasticity. Increasing the switches' ports means an exponential scaling of PMs in the fat-tree, and the over-time elasticities for the VCs will have a large growth. As shown in Fig. 9, when the size of the fat-tree is not very large ($\theta = 4$ and $\theta = 6$), the advantage of online scheduling with prediction is not obvious. When the size of the fat-tree is scaling, ($\theta = 8$, $\theta = 10$, or $\theta = 12$), the gap between these two solutions increase with the scale of the fat-tree. The insights of resource allocation for S-OMVCS and A-OMVCS are similar, but the main difference is in the resource reservation. We compare our A-OMVCS algorithm with the S-OMVCS algorithm for the asynchronous condition. Fig. 10 presents the performance for A-OMVCS by calculating the over-time elasticity, and the gap between A-OMVCS and S-OMVCS in over-time elasticity is not obvious. However, the percentage of the reservation resource sharply decreases to 45% with an increase in the scale of the DCN, as shown in Fig. 11.

VIII. CONCLUSION

This paper considers elastic scaling for existing VCs to maximize elasticity in the DCN with the constraint of communication cost. We achieve this using a resource allocation scheme, VCS, which comes with provable optimality guarantees for single VC scaling. After that, we extend our scheme to scale for multiple VCs, and we prove that scaling multiple VCs for the over-time elasticity maximization problem is NP-hard. We propose heuristic algorithms MVCS, S-OMVCS, and A-OMVCS for both offline and online conditions in the multiple VC scaling problem. This paper focuses on the condition that VCs scaling on both computation and communication resources, which can also be adapted to each individual resource. Extensive simulations demonstrate that our elastic VC scaling placement schemes outperform existing state-of-the-art methods in the DCN in terms of elasticity.

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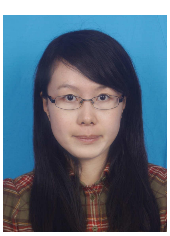

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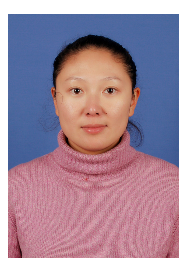

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