A novel cooperative resource provisioning strategy for Multi-Cloud load balancing

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A B S T R A C T

The paradigm of cloud computing has heralded a new avenue of computing, offering benefits of increased data accessibility with low cost. Continuous Writing Applications (CWA) (e.g., augmented online services for Health Care) have specific requirements on data storage, computation and bandwidth, thus are cost-sensitive with limited budgets and time. Herein, we propose an architecture of multi-cloud service provider (CSP) or “Multi-Cloud” to provide services to CWA, and design a novel resource scheduling algorithm to minimize the system cost. The system models of classic CWAs to tackle the resource requirements of users on MCP are exploited. The study can help to understand the characteristics of different resources and conclude Multi-Cloud being the most attractive to many CWA implementations. Interconnections of multiple CSPs and their load paths (i.e., data passing through possible interconnections) are introduced. We then formulate the problem and present optimal user scheduling based on Minimum First Derivative Length (MFDL) of system load paths. Theoretical analysis demonstrated that the solutions with minimized costs can be achieved by the proposed algorithm, termed “Optimal user Scheduling” for Multi-Cloud (OSMC). Through rigorous simulations regarding different influencing factors, the proposed strategy has proven to be scalable, flexible, and efficient in many practical scenarios.

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1. Introduction

Subscription based or pay-per-use service business model known as Cloud Computing has gained significant importance over the past years. Cloud computing has numerous advantages, including provisioning of computing capacities, wide and heterogeneous network access, resource pooling and rapid elasticity with measured services [17,22,24]. Most applications running on local PCs have been migrated to Cloud Service Providers (CSPs), such as Amazon EC2 [28], Windows Azure [26], IBM’s Blue Cloud [1], due to many advantages, e.g., providing flexible costs and improving data and application availability. In [27], it was suggested that cloud computing services can allow fast access to applications as well as reduce infrastructure costs, even for small and medium companies.

The primary service offered by CSPs is Cloud Data Storage. Instead of storing data on local machines, users can store data on CSPs that allow easy data retrieval from any geographical region via the Internet. Various IT giants have provided limited free services and storage spaces for data uploading such as pictures and videos. Besides, the ability to share the data with other users is allowed through Cloud Data Storage, such as Amazon S3, Microsoft SkyDrive, and Apple’s iCloud. CSPs also provide more service options for users who are willing to pay for extra spaces and more corresponding function utilities. Nowadays, with the emergence of Wireless Sensor Networks (WSNs), mobile networks, Internet of Thing (IoT) [5], more and more data and information “ensed” from the environment can be stored and processed on CSPs, and then shared by the authorized entities.

Fig. 1 illustrates four main categories of services provided by CSPs, that are detailed in the following.

(a) Surveillance System: Due to convenient storage and retrieval functions, more and more deployed surveillance systems have adopted CSPs to store the round the clock video recordings, instead of the traditional way using local storage devices. Additional services provided by CSPs include video surveillance search, customized pre-alarms, as well as flexible and convenient methods for viewing, analyzing and extracting information from...
controls all resources, including both local resources and that each of the CWA as that involves resources requirements in terms of delivering the CWAs services. There are some service demands for the abovementioned in this paper, “Multi-Cloud” is proposed to Amazon is not responsible for cloud service availability. To tackle the user’s cloud services may terminate at any time. In addition, services may be unavailable occasionally [28]. This may lead to that when collecting massive data, the provided cloud services may be unavailable occasionally [28]. This may lead to that the user’s cloud services may terminate at any time. In addition, Amazon is not responsible for cloud service availability. To tackle the above limitation, in this paper, "Multi-Cloud" is proposed to assure service availability that can satisfy particular requirements of CWAs. We also reduce the operating cost of the CSPs that deliver the CWAs services. There are some service demands for each of the CWAs that involve resources requirements in terms of storage capacity, bandwidth, and CPU cycles. The CSPs completely controls all resources, including both local resources and that provided by the other CSPs, then provided as services of the CWA to the users under the term of a solo CSP. It is assumed that the resource utility costs may vary for the same service for users based on geographical distribution. To assure data availability, we assume that same data from a single user will be stored by at least two CSPs. In this way, each CSP can build its particular virtual Multi-Cloud or "multiple Clouds" and organize the resources flexibly to meet the needs of increasing users, as well as ensure a higher Quality of Service (QoS).

A worth-seeing problem in the field of Multi-Cloud can offer services to massive CWA users around the world: "how can the CSPs organize the resources of Multi-Cloud, to reach the lowest utility cost for each customer?" Herein, a multi-tuple mathematical model is formulated to describe the key concerns, including users’ resource requirements, utility costs of the CSPs, as well as inter-cloud communications. Additionally, based on the model, we propose a novel algorithm of cooperative multi-cloud load-balancing, which can meet all the resource requirements of users while achieving the minimum cost per user.

The rest of the paper is organized as follows. The relevant research work is discussed in Section 2. Section 3 describes the CWA model and formulates the optimization problem. In Section 4, our strategy for optimal load-path search in Multi-Cloud is proposed. In Section 5, we introduce our proposed algorithm in detail, termed Optimal user Scheduling for Multi-Cloud (OSMC). Sections 6 and 7 cover the experimental results and conclusions.

### 2. Related work

Many online applications can be classified as CWAs, such as surveillance systems, e-Health, and Internet-of-Things [5], etc. These applications continuously generate massive data that require to be transported, stored and analyzed in real time. Each application requires three basic factors, namely communication bandwidth for data transportation, large data storage capacity, and computational power to analyze the collected data. Many traditional CWAs are restricted by small scale systems. In order to set up a system that can satisfy all the requirements independently, expensive devices, such as cameras, sensors, wires, central control devices, and pre-compiled programs need to be planted to provide improved storage space and computational capacities [15]. However, the scalability of such systems is extremely poor.

With the development of cloud computing [21] and big data processing [10,11], the basic requirements of CWAs can be satisfied by CSPs. Many novel business models targeting at CWA markets have emerged recently, such as Camba for surveillance systems [12]. With the support of Cloud computing, CWAs can evolve from closed, independent systems to open, scalable platforms. The success of CWAs on cloud computing mainly depends on two factors namely operational cost and reliability. It is widely recognized that the resource utilization cost and scheduling in networked systems entails strategic significance, and many seminars and working group meetings have explored the subject for a long period [9,13,29].

Recently, more and more research work explore the specific solutions provided by the major Cloud/Edge provider and it is difficult to fully exploit different Clouds/Edges concurrently. Easy-Cloud is proposed in [4], which is an easy and effective toolkit and user interface able to not only interact with multiple and different Cloud/Edge platforms at the same time but also to provide a rule-based engine where the user can specify what to do in real-time when the workload of the services running on the Clouds/Edges becomes under-utilized (e.g., switch-off the service to save money) or over-utilized (e.g., switch-on new computational resources to overcome the increased workload).
Many research efforts have been conducted on resource utilization cost models in the literature, such as learning curve [14], Divisible Load Theory (DLT) [8], and queueing models [7]. Cost of use and supply issues are still an arduous task in cloud computing. CSPs provides a service template menu which consists of various resources, such as CPU, storage, bandwidth, and memory. Difficulty in resource provisioning increases since various requirements may emerge from various users on each of these dimensions [14]. Although Cloud computing brings in many benefits such as low cost and data accessibility, however, due to concerns such as the risks of service unavailability and potential malicious attacks, dealing with a “single cloud” providers is expected to be no longer preferred by users. Therefore, the focus has recently shifted to “multi-clouds”, or in other words, “inter-clouds”, or “cloud-of-cloud” [3,16]. Herein, we study the collaboration of Multi-Cloud for data backup with aims to enhance system reliability.

3. System model, notation and problem definition

This study focuses on CSPs that provide Infrastructure-as-a-Service (IaaS). IaaS is a service model providing an infrastructure of the computer for supporting enterprise operations. Typical IaaS services include Microsoft Azure, Amazon EC2, Rackspace, and GoGrid. One CSP can be assigned as the Chief Cloud of the multiple Clouds. Furthermore, every CWA requires at least two CSPs for data storage to improve data availability. It is assumed that the Chief Cloud schedules the resources of other CSPs. Let \( C_0 \) denote the set of CSPs. \( C_{SP} \) is introduced to build the Multi-Cloud accordingly, which can be the Chief Cloud. We have \( C_0 = \{ C_{SP}, C_{SP}, \ldots, C_{SP} \} \). Each \( C_{SP}, k = 0, 1, 2, \ldots, n \), has certain resources. A tuple is used to denote the resources \( R_{k} = [B_k, S_k, C_k] \), where \( B_k \) denotes the bandwidth, \( S_k \) denotes the storage space, and \( C_k \) denotes the computational capability of \( C_{SP} \). \( R_{k} = [B_k, S_k, C_k] \) denotes the upper-bound of the resources that a CSP can offer to \( C_{SP} \). A vector \( R_k = [P_{B_k}, P_{S_k}, P_{C_k}] \) is used to represent the utility cost functions of the \( C_{SP} \) for the resources in terms of bandwidth, storage, computing, respectively. It is assumed that the \( C_{SP} \) involves \( m \) users, where \( m \gg n \).

According to the service packages, the users can be divided into \( J \) categories. For example, \( C_{SP} \) can provide storage service packages for one day, one month, or one year, and charge different service fees. All users are assigned some priorities on the basis of category classifications. Higher priority of user infers that the user has paid more for the services, thus in return gaining access to more data storage in the system. Let \( \mathcal{U} = \{ u_j \} \) denote the set of users within the \( C_{SP} \), where \( u_j \) denotes the user \( j \) with a priority of \( j = 1, \ldots, J \) for user \( i = 1, \ldots, m \). Each user \( u_j \) has some basic requirements in terms of bandwidth, storage, and computation that can be denoted as \( r_j = [B_j, S_j, C_j] \). All the user requirements must be satisfied by \( C_0 \) in order to successfully allocate resources.

As shown in Fig. 2, the main focus is on the communications of the inter-cloud and intra-cloud. We assume that if two CSPs are connected by a direct communication link, then CSPs are the neighboring nodes of each other. We use \( \mathcal{X} \) to denote the set of neighboring nodes of \( C_{SP} \), e.g., in Fig. 2, \( \mathcal{X}_3 = \{ C_{SP}, C_{SP}, C_{SP} \} \). We use \( L_{u}, l_j \) to denote the communication bandwidth between \( C_{SP} \) and \( C_{SP} \), and \( B_{u}, b_k \) to denote the communication cost on a link \( L_{u}, l_j \). If two CSPs have no direct link, then the CSPs need two or more network links to set up the communication paths.

3.1. Customer’s utility cost model of CWA

Two CSPs are required for each customer \( i \), \( C_{SP} \) and \( C_{SP} \). When the customer \( i \) subscribes a CWA package \( j \), then \( C_{SP} \) decides which \( C_{SP} \) should be connected directly to \( u_i \). Simultaneously, another CSP is required to store the data sent from \( C_{SP} \) as a backup, which is denoted as \( C_{SP} \). It is assumed that the \( C_{SP} \) only select one CSP from \( N_{iCWA} \) as the \( C_{SP} \). The following equation is obtained for utility cost function of customer \( i \)

\[
f_{\text{cost}}(i) = f_{\text{cost}}(i, C_{SP}, C_{SP}) + f_{\text{cost}}(i, C_{SP}, C_{SP}) + f_{\text{cost}}(i, C_{SP}, C_{SP}) + f_{\text{cost}}(i, C_{SP}, C_{SP}), \tag{1}
\]

subject to:

\[
r_j^i \leq R_{iCWA}, b_j^i \leq B_{iCWA}, S_j^i \leq S_{iCWA}.
\tag{2}
\]

A list of notations with their descriptions is presented in Table 1.

Supposing \( R_{iCWA} \) is used to denote the resource required by customer \( i \) on \( C_{SP} \), then we get \( R_{iCWA} = [B_i, S_i, 0] \), where the computational requirement is zero. Consequently, the cost function of (1) can be transferred to:

\[
f_{\text{cost}}(i) = r_j^i \cdot P_{T}^i + r_j^i \cdot P_{T}^i, \tag{3}
\]

with \( r_j^i \leq R_{iCWA}, r_j^i \geq R_{iCWA}, \) and \( C_{SP} = C_{SP} \) are the neighboring CSPs.

3.2. Problem formulation

In this section, the problem will be formulated in detail. We first obtain the system cost utility function of all of the users on \( C_0 \) as:

\[
F(C_0, \mathcal{U}) = \sum_{i=1}^{m} f_{\text{cost}}(i)
\]

subject to:

\[
R_{k \in \mathcal{X}CSP}, C_0, \leq R_{k}.
\tag{5}
\]
From (5), it is observed that the utility cost function of CSP, denoted as $P$, can be considered as one of the critical factors that impact the resource scheduling for the Multi-Cloud. $P$ can be divided into two types of functions, i.e., linear or non-linear functions [6]. According to Divisible Load Theory (DLT) [8], linear functions represent computation and communication utility cost functions. However, linear functions are simplified problem formulations. For real-time scenarios (e.g., system queue-cost functions. However, linear functions are required to quantify the utility costs [30]. Resource scheduling algorithms vary with different cost functions. The paper proposes a general method to minimize the total utilization cost of Multi-Cloud using various cost functions.

With reference to Fig. 2, the problem considered in this paper can be elaborated as follows. The Multi-Cloud that provides the CWA services, has a user pool with $m$ users and each of the user has different resource requirements. Let CSP be the user broker also known as the Chief Cloud. A user broker is the broker which collects the resource status from all the clouds, keeping a log of the resource cost of each of the cloud. The user broker has two functions:

- One is to schedule the users from the user pool.
- One is to make decision on the CSP$_{i\rightarrow edge}$ and CSP$_{i\rightarrow back}$ for each of the user.

For every user provided with CSP$_{i\rightarrow edge}$ and CSP$_{i\rightarrow back}$, they are neighboring CSPs that are connected by direct communication links. The aforementioned scheduling must satisfy the two main constraints: (a) The resource requirements of all the users are to be satisfied by the Multi-Cloud; and (b) the sum of all the users’ resources that a CSP provides must not exceed the actual available resources.

4. Optimal load paths within Multi-Cloud

With reference to Section 3, when a CWA is registered, the Multi-Cloud must seamlessly deliver two connected CSPs to the user, which are a Chief CSP and a data backup CSP. With reference to 2, if CSP$_2$ is a user’s Chief CSP, then two potential load paths are available, namely (CSP$_2$, CSP$_i$) and (CSP$_2$, CSP$_j$). Thus, the complexity of the potential load paths for each of the user is given by $O(nk)$, where $n$ is the number of CSPs in the system and $k$ is the average number of adjacent CSPs. Let $P_0$ denote the set of all potential paths within the Multi-Cloud. After the definitions, we shall analyze the cost of all the load paths in the following.

4.1. Cost of single CSP and load paths

Each CSP can be considered as either Chief CSP or data backup CSP. With reference to Eqs. (1) and (3), it can be noted that computational resources are not required for the backup CSP. It is assumed that a set of users, $U_i$, that require services from CSP can be further classified into two sub-sets $U_{i\rightarrow edge}$ and $U_{i\rightarrow back}$, where $U_{i\rightarrow edge}$ denotes the set of users using CSP as the Chief CSP and $U_{i\rightarrow back}$ denotes the set of users using CSP as the data backup CSP. Further it can be noted that $U_{i\rightarrow edge} \cap U_{i\rightarrow back} = \emptyset$ and $U_{i\rightarrow edge} \cup U_{i\rightarrow back} = U_i$ hold. Referring to (15), the utilization cost function of a single CSP can be obtained as:

$$F_i(U_i) = \sum_{\forall i \in U_{i\rightarrow edge}} (r_{i\rightarrow edge}^j \cdot P_{i\rightarrow edge}) + \sum_{\forall i \in U_{i\rightarrow back}} (r_{i\rightarrow back}^j \cdot P_{i\rightarrow back}).$$

(6)

Supposing a new user, $u_i$, select CSP$_i$ as the Chief CSP or data backup CSP, therefore the new set of users $U_i$ is updated to $U_i' = U_{i\rightarrow edge} \cup U_{i\rightarrow back}$ or $U_i' = U_{i\rightarrow edge} \cup U_{i\rightarrow back}$, respectively, where $U_{i\rightarrow edge} = (U_{i\rightarrow edge} - u_i)$ and $U_{i\rightarrow back} = (U_{i\rightarrow back} - u_i)$. According to (6), the new utilization cost of the CSP$_i$ because of the new user, $u_i$, can be obtained, namely $F_i(U_i')$.

Suppose the load path of $u_i$ is determined to be (CSP$_{i\rightarrow edge}$, CSP$_{i\rightarrow back}$) by the user broker. CSP$_{i\rightarrow edge}$ and CSP$_{i\rightarrow back}$ function as the Chief and a data backup CSP, respectively. We use $F_n$ to represent the cost of $u_i$ along a path $P_n$, where $P_n$ is path (CSP$_{i\rightarrow edge}$, CSP$_{i\rightarrow back}$). Consequently, we obtain:

$$F'_i = F_i(U_i') = F_{i\rightarrow edge}(U_{i\rightarrow edge}' - u_i) - F_{i\rightarrow edge}(U_{i\rightarrow edge} - u_i)
+ F_{i\rightarrow back}(U_{i\rightarrow back}' - u_i) - F_{i\rightarrow back}(U_{i\rightarrow back} - u_i).$$

(7)

It is worthy to notice that $r_{i\rightarrow edge}^j P_{i\rightarrow edge} + r_{i\rightarrow back}^j P_{i\rightarrow back} = F_n, \forall i \in U_i$. According to (7), we can re-formulate the objective function described in (5), as follows:

$$F(C_0, U_i) = \sum_{i=1}^{m} (r_{i\rightarrow edge}^j P_{i\rightarrow edge} + r_{i\rightarrow back}^j P_{i\rightarrow back})$$

$$= \sum_{i=1}^{m} F'_i,$$

(8)

where CSP$_{i\rightarrow edge}$ and CSP$_{i\rightarrow back}$ are neighboring CSPs.

Thus, it can be found that each user has multiple load paths with various costs. In order to minimize the utilization cost of the entire system, the optimal cost path for all the users shall be determined one after another. For this reason, we introduce the definition of the First Derivative Length (FDL) of the load path as follows:

$$F'_i = \sum_{i=1}^{m} (r_{i\rightarrow edge}^j P_{i\rightarrow edge} + r_{i\rightarrow back}^j P_{i\rightarrow back})$$

$$= \sum_{i=1}^{m} \frac{\partial (U_{i\rightarrow edge} - u_i)}{\partial r_{i\rightarrow edge}^j} P_{i\rightarrow edge} + \frac{\partial (U_{i\rightarrow back} - u_i)}{\partial r_{i\rightarrow back}^j} P_{i\rightarrow back}.$$

(9)

Combining (1), (9), $r_{i\rightarrow edge}^j = (b_{i\rightarrow edge}, s_{i\rightarrow edge}, c_{i\rightarrow edge})$, and $r_{i\rightarrow back}^j = (b_{i\rightarrow back}, s_{i\rightarrow back}, c_{i\rightarrow back})$, we obtain:

$$F'_i = \sum_{i=1}^{m} \left( \frac{b_{i\rightarrow edge}}{\partial b_{i\rightarrow edge}} + \frac{a_{i\rightarrow edge}}{\partial a_{i\rightarrow edge}} + \frac{c_{i\rightarrow edge}}{\partial c_{i\rightarrow edge}} \right).$$

(10)
\[ + fcost(i, S_{i-back}) + \frac{\partial fcost(i, B_{i-back})}{\partial b_i} b_i + fcost(i, B_{i-back}) + \frac{\partial fcost(i, S_{i-back})}{\partial s_i} s_i. \] (10)

4.2. Optimal load path for each user

For every user \( u_i \), among all the \( P_i \) paths, there must be at least one path, denoted as \( P_0 \), with minimum FDL. This path is defined as the minimum first derivative length (MFDL). The following theorem is from [29].

**Theorem 1.** The set of \( \bar{P}_i \), where \( \forall u_i \in \lambda_{\ell} \), is an optimal solution to (5) if and only if each user \( i \) chooses the path with the MFDL among the set of all potential paths, \( P_0 \). Moreover, if \( fcost \) is assumed to be convex, then \( \bar{P}_i \) is optimal if and only if the path with the MFDL in \( P_0 \) provides a service to \( u_i \).

From Theorem 1, it is observed that an optimal solution results only if users’ requests travel along the MFDL paths among \( P_0 \). The optimal load path for the users can be determined one by one within the system. Theoretically, the sequence of the user scheduling has no bearing on the final results. In the DLT, the load can be arbitrarily divided and the entire system can be eventually balanced according to the optimal solutions. However, in this paper, the user service load cannot be divided arbitrarily to be served by parallel load paths. To further explain the aforementioned, a situation is considered where a few users require large amounts of data. If such users are scheduled at the end, a system imbalance will be observed. Thus, user scheduling is a necessity. Herein, it is assumed that users have been divided into several categories with different priorities, the users can be scheduled according to required service volume. The scheduling sequences are considered as follows:

- Sequence A (SA): Select a user amongst the ones not yet scheduled randomly;
- Sequence B (SB): Sort and assign the users from low to high according to the priorities, and select the un-selected users one by one in the same priority randomly, and;
- Sequence C (SC): Requires two sorting sequences. First, the users are sorted according to their priorities. Second, sort the users with the same priorities on the basis of amount of required services. The user is then selected from the highest priority.

In the following section, an algorithm is proposed that can schedule the users to reach the minimum utilization cost of the entire system.

5. The proposed algorithm

Each user will be assigned to a load path by the user broker (CSP) as shown in Fig. 2. The basic idea is to determine the MFDL path for all the users within the system one by one according to a predefined sequence, such as SA, SB, and SC, to minimize the utilization cost of the entire system. In the sub-sections, an algorithm is proposed to reach a near optimal solution of (8). This is referred to as the “Optimal user Scheduling for Multi-Cloud” (OSMC).

5.1. Design of OSMC

The pseudo code of the proposed algorithm can be described as follows (refer to Table 2). In the initialization phase, a set of load paths is constructed, \( P_0 \). Each CSP within the system can build a load path with any neighboring CSP. Let the number of CSPs within the system be \( n \). Assuming the Multi-Cloud is fully-connected, each CSP has \( n-1 \) load paths. Therefore, there will be a total of \( n \cdot (n-1) \) load paths within the system. Table 3 presents the pseudo code of the Sub-algorithm of Load Path Finding (SaLPF). It constructs a set of load paths, \( P_0 \), within the system. After the construction of \( P_0 \), the FDL of each path according to (10) obtained. The minimum among \( P_0 \) is then determined. If two or more load paths have the same MFDL, then one is chosen randomly as the MFDL. The users should be sorted in \( \lambda_{\ell} \) following the sequences of SA, SB, or SC (See Table 2).

The target of the algorithm is to determine the optimal path for each user and guarantee that the resources of the load path satisfy the user’s requirements. The main loop (refer to Table 2) focuses on three procedures as follows.

1. **Sort the load paths in** \( P_0 \) **according to the FDL from the lowest to the highest;**
2. **Examine whether the load path can satisfy the requirements of the user.** If the resources of the user cannot be satisfied along the load path, examine the load path with the next minimum FDL within the available load paths until the set of available load paths becomes empty; and
3. **If the optimal load path for the user has been determined,** update the FDL of all the load paths effected by the selected load path.

There may be some users whose resource requirements cannot be satisfied due to the limited resources of the Cloud-of-Clouds. In such a case, the algorithm will send a warning for system
extension, instead of rescheduling all of the users to meet the requirements.

5.2. Case studies of load paths

In this section, the analysis of a single load path is illustrated as an example. The cost functions of bandwidth, storage, and computation for each CSP are initially constructed. Referring to (3), it is assumed that for CSP_k, \( P_k = \{P_{b_k}(b_k), P_{s_k}(s_k), P_{c_k}(c_k)\} \), where

- \( P_{b_k}(b_k) \) denotes the bandwidth cost function, where \( b_k \) is the bandwidth used;
- \( P_{s_k}(s_k) \) denotes storage cost function, where \( s_k \) is the total utilized storage space;
- \( P_{c_k}(c_k) \) denotes computation cost function, where \( c_k \) is the computation capacity used in CSP_k.

Following the assumptions that the communication cost can be modeled as \( M/M/1 \) system \([7,19,29]\) and the communication cost per unit time for CSP_k is \( \alpha_k \). Therefore, \( P_{b_k}(b_k) \) can be formulated as

\[
P_{b_k}(b_k) = \frac{\alpha_k}{\mu^c_k} - b_k,
\]

where \( \mu^c_k \) is the communication processing rate of CSP_k in KBPS (kilobit per second).

Further assumptions are made that the storage cost is independent on \( s_k \), and we can obtain

\[
P_{s_k}(s_k) = \beta_k,
\]

where \( \beta_k \) is a constant in the unit cost per gigabytes.

As per the discussion in \([9]\), although an \( M/G/n \) queueing system are taken into consideration in cloud computing, the \( M/M/n \) system is the only model that accommodates an analytical and closed-form expression of the probability density function to calculate the waiting time of a new service request. Therefore, the computational cost can be modeled as \( M/M/n \) system. The computational cost per unit time for CSP_k is assumed to be \( \gamma_k \). Following \([9,29]\), we can obtain \( P_{c_k}(c_k) \) as

\[
P_{c_k}(c_k) = \gamma_k \cdot Tc_k = \frac{\gamma_k P_0}{n_k \mu^c_k} - c_k,
\]

where \( P_0 = P(\text{Queueing}) = \rho_0 (n_k \rho_k)^n_k / n_k \mu^c_k (1 - \rho_k) \), \( \rho_0 = \frac{c_k}{n_k \mu^c_k}, \rho_k < 1 \).

In (14), \( n_k \) is the number of virtual machines that can provide the computation services to the users in CSP_k, \( \mu^c_k \) is the computation processing rate of the virtual machines in MIPS (million instructions per second), and \( \rho_0 \) is the probability of no request waiting in the queue of the node, which is given as

\[
p_0 = \left( \frac{n_k \rho_k}{\mu^c_k} \right) + \left( \frac{n_k \rho_k}{\mu^c_k (1 - \rho_k)} \right)^{-1}.
\]

The unit of (13) is unit cost per MIPS.

We have two kinds of users within the system and we assume that the resource requirements of the users with priority one is denoted as \( r^1 = [b^1, s^1, c^1] \). For example, if \( r^1 = [200, 100, 20] \), then that means the users of priority one require 200 kbps bandwidth, 100 G storage space, and 20 MIPS computation capacities. Therefore, from (8), (12), and (13), \( P_k = \{P_{b_k}(b_k), P_{s_k}(s_k), P_{c_k}(c_k)\} \) can be constructed for each CSP within the system and we can obtain the closed-form of the load path by using (9) for users with priority equal to one.

Following assumptions are also made:

- Users can be classified into multiple categories with different resource requirements;
- The users of the same category have the same resource requirements, that means \( x^j = x^j, x \neq y \) hold.

In (9), we can observe that \( r^j \) may vary with different \( j \), and if we consider only a single user, then the calculation will increase rapidly. Therefore, in OSMC we calculate the FDL of each of the load path for users with the same priority \( j \) by using \( r^j \). We also can further simplify the calculations by using \( r = [\bar{b}, \bar{s}, \bar{c}] \), instead of \( r^j \) in (9), where

\[
\bar{r} = \frac{1}{m} \left( \sum_{i=1}^{m} b^i, \sum_{i=1}^{m} s^i, \sum_{i=1}^{m} c^i \right),
\]

for all load paths in the system.

From the above discussion, it was observed \( fcost \) in (5) is the sum of communication cost (convex function), storage cost (linear function), and computational cost (convex function). Hence, \( fcost \) in this model is also a convex function and the condition of Theorem 1 can be guaranteed.

5.3. Rate of convergence

Our algorithm is based on Newton’s method \([25]\). We denote \( h(r^k) = D(r^k) \) for iteration \( k \). If an optimal solution is at point \( \bar{r} \), then we have \( h(\bar{r}) = 0 \). Alternatively, we have:

\[
\phi(r^k) = r^k - \alpha \frac{h(r^k)}{h'(r^k)}
\]

By the mean value theorem, we obtain:

\[
r^{k+1} - \bar{r} = \phi(r^k) - \phi(\bar{r}) = \phi'(\xi_k)(r^k - \bar{r}),
\]

where \( \xi_k \) lies between \( r^k \) and \( \bar{r} \). Then

\[
|n^{k+1} - \bar{r}| = \frac{|h'(\xi_k)h(\xi_k)|}{|h'(\xi_k)|^2}|r^k - \bar{r}|
\]

and

\[
|h(\xi_k)| = |h(r^k) - h(\bar{r})| = |h'(\eta^k)||\xi_k - \bar{r}| \leq |h'(\eta^k)||r^k - \bar{r}|
\]

where \( \eta^k \) lies between \( \xi_k \) and \( \bar{r} \). Hence:

\[
|r^{k+1} - \bar{r}| \leq \frac{|h'(\xi_k)h(\eta^k)|}{|h'(\xi_k)|^2}|r^k - \bar{r}|^2
\]

Let \( \beta = \sup \frac{|h'(\xi_k)h(\eta^k)|}{|h'(\xi_k)|^2} \),

then

\[
|r^{k+1} - \bar{r}| \leq \beta|r^k - \bar{r}|^2
\]

Hence the convergence of our algorithm is \( 2 \), which exhibits a super-linear convergence.

6. Performance evaluation and discussions

6.1. Assumptions for simulations

In our simulations, we employ a discrete-event approach to model, simulate, and evaluate the system \([18]\). 10 CSPs are considered for serial simulations. For the simulations different settings of Multi-Cloud are taken into consideration. A number of other CSPs ranging from one to nine are randomly selected as neighboring CSPs for each CSP_k to construct the set of S_k within the system. The resources, \( R_{ik} \), of CSP_k are generated within the following ranges randomly. The bandwidth of the CSPs is set to
the value randomly selected from [10, 100], with the unit in gigabit per second (GBPS). The storage space of CSPs is set to the value randomly generated from [2, 200] PB. Then, the number of virtual machines in CSPs is set to the value randomly selected from [1000, 100000], and the value of $\mu_k$ is set to the random value from [50, 500] MIPS. Further, it is assumed that the performance of all the virtual machines within the same CSP remain the same. In the previous section, the costs of each of the unit resource in the CSPs have been defined as $\alpha_k$ for bandwidth, $\beta_k$ for storage, and $\gamma_k$ for computation, which are set to the value randomly chosen from [1, 100] with the unit of cost per 24 hours.

In each of these simulation experiments, the number of users is increased till no more users could be added to the system. Each user, categories were determined randomly between one to four using uniform distribution.

To compare the performance with OSMC, the simulations use round-robin algorithm [7] as the benchmark algorithm. Round-robin algorithm is selected as it is simple and is efficient for job scheduling. In the round-robin algorithm, a list of all paths is selected one after another for each user, until no more users can be added to the system.

6.2. Experiments on small size of Multi-Cloud

In this set of experiments, we randomly generate a Multi-Cloud with 10 CSPs. The parameters assumed for all CSPs are as shown in Table 4. We generate a set of users with random classes and schedule the users by using the OSMC and round-robin (RR) algorithm, respectively. Initially, only the SA sequence is used. In the later sections the effect of the sequences will be discussed by carrying out further experiments.

For simulations purposes, the number of users are generated from one to infinite. The simulation is stopped until no load paths are available for the users. The upper bound utilizations of bandwidth, storage, and computation capability were set to 0.95. For every set of users within the experiments, the average utility costs per user are recorded with the increasing of user numbers, until the end of the procedures, and the results are illustrated in Fig. 3(b). It was observed that when the number of users raises up to 754,054, both OSMC and RR terminate the scheduling. It can be inferred that the current system settings can support only 754,054 users. The resource utilizations of all the CSPs are elaborated when the system cannot support adding more users, as reported in Table 5.

In Table 5, computation capability is observed to be the bottleneck of the entire system. We can find that in either OSMC or RR $\rho_k = c_k / (\mu_k \cdot \mu_k)$ has reached the upper limit of the system, namely 0.95. The utilizations of other resources (e.g., storage and bandwidth) are at very low levels, rarely exceeding 10%.

In Fig. 3(b), since the utilization of bandwidth and computation are very low when the number of users is at a very small
Table 5
The utilizations of resources in CSPs.

<table>
<thead>
<tr>
<th>Types</th>
<th>Utilizations of CSP 1 to CSP 10</th>
</tr>
</thead>
<tbody>
<tr>
<td>OSMC (ρk)</td>
<td>0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95</td>
</tr>
<tr>
<td>RR (ρk)</td>
<td>0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95 0.95</td>
</tr>
<tr>
<td>OSMC (band.)</td>
<td>0.001 0.004 0.007 0.011 0.012 0.013 0.039 0.041 0.448 0.075</td>
</tr>
<tr>
<td>RR (band.)</td>
<td>0.012 0.009 0.016 0.02 0.029 0.029 0.053 0.036 0.93 0.017</td>
</tr>
<tr>
<td>OSMC (storage)</td>
<td>0.003 0.018 0.031 0.013 0.016 0.021 0.029 0.066 0.024 0.932</td>
</tr>
<tr>
<td>RR (storage)</td>
<td>0.046 0.043 0.076 0.024 0.035 0.047 0.04 0.06 0.051 0.21</td>
</tr>
</tbody>
</table>

Fig. 4. Performance comparisons of algorithms with sequences SA, SB, and SC.

scale, the user cost will account for the storage costs. Thus, for each user, the OSMC searches for the best load paths, and ensure the lowest costs. The RR considers whether resources can support users, and schedules users one by one. However, the resources utilizations along the paths are not considered. The RR will allocate more and more users to certain paths which will lead to overloading while, many other paths remain very low utilizations. With the number of users increasing, the lowest resources in the system soon dominate the costs, which then rises rapidly. Herein, the CSP with the lowest computation power is the lowest resource in this setting. Hereafter the path with the lowest resources turn out to be saturated, the load paths with the second, third lowest resources become saturated successively. This clarifies that the costs of the RR grows steadily when the number of users reaches certain small point. Since the cost per user is considered, the cost may fluctuate when more users join in the system, as indicated in the figure. It is anticipated that the users with lowest resources along the paths will possess much more costs compared with the average. By contrast, users are considered equally in the proposed OSMC algorithm which promotes nearly the same costs for each user in the system. Merely after the number of users increases around 400,000 that the cost begins to rise slightly until the entire system becomes saturated. It may be noted that when some thresholds of resources are set, and single type of resources are the bottleneck in the system, both the RR and OSMC algorithms can take full usage of the entire system.

6.3. Experiments on medium to large size of Multi-Cloud

To observe the scalability of the OSMC algorithm, in this set of experiments, the OSMC is compared with RR on Multi-Cloud, the size of which is large to medium. 50 Multi-Cloud are randomly generated. The topology of the system is generated randomly and for each CSP, a range of one to nine neighboring CSPs may exist. Similar to Section 6.1, the computation of the system is at first set to be the system bottleneck and then, balance the recourses to examine the performance of the OSMC and RR algorithms.

Referring to Fig. 3(a), which are the results of large to medium size systems when the bottleneck is from computation capacity, it is observed that compared to the small size of Multi-Cloud, the system can support much more users. For small number of users, the cost per user of the RR shows a rapid increase and almost reaches the peak around $0.2 \times 10^6$, which is $0.6\%$ of $5.8 \times 10^6$ (i.e., the number of total users). On the other side, in most cases, the cost per user of the OSMC can be maintained within a very low scale, and reaches one when the number of users surpasses $5 \times 10^6$; whereas for the RR, the cost per users again retains around 50.

The computation capacities of CSPs are balanced out with the same methods used in Section 6.1 and carry out the experiments again. The results are presented in Fig. 3(b), where the OSMC can support 28, 196, 493 users and the RR can merely support 26, 388, 862 users. It also indicates when the cost of users exceeds one for both the OSMC and RR algorithms.

From these experiments, it can be concluded that our proposed OSMC is efficient, flexible and extensible, and can be applied for large scale systems.

6.4. Effects of scheduling sequences on OSMC and RR algorithms

As mentioned earlier, in our simulations, four categories of users are generated that have distinct resource requirements or priorities. Given a set of users, they can be scheduled one by one by the algorithms, and follow certain pre-defined sequences, e.g., SA, SB, and SC, as presented in the previous section. Furthermore, we carry out several experiments based on small size
Multi-Cloud for the OSMC and RR algorithms, to examine the effects of scheduling sequences on the final results. We assume that we have 100,000 users and the number of each type users is set to 25,000. We report the final results of the OSMC and RR algorithms in Fig. 4.

In Fig. 4(a) OSMC-SA, OSMC schedules the users following the SA sequence, which performs steadily and the cost per user shows a slight fluctuation, which is around $4 \times 10^{-3}$ units. For OSMC-SB, the users with the lowest priorities are scheduled firstly, as more and more users are scheduled, the cost per user increases. On the other side, for OSMC-SC, in which the users with the highest priorities are scheduled firstly, the cost per user decreases. The three curves converge to a single point, until all users have been scheduled. In Fig. 4(b), we also observe that when all of the users have been scheduled, the curves of RR-SA, RR-SB, and RR-SC converge to a point, which is around $1 \times 10^{-4}$.

From these experiments, we can find that there is no or very small effect of scheduling sequences on the final results. Because in the Multi-Cloud, millions of users are considered, it is impossible to re-schedule all of the users that have been resolved for some newcomers. It is very interesting to point out that because the user sequences have no effect on the final results, our proposed OSMC algorithm also has potential usage in dynamic scenarios.

7. Conclusions and future work

This study proposed an optimal user scheduling algorithm for CWA applications, named the Optimal user Scheduling for Multi-Cloud (OSMC). Various factors were considered, including the user requirements of bandwidth, storage, and computation, the resources of CSPs that can provide, CSPs for data backup, and the configurations of Multi-Cloud, cost models of CSPs. By using the M/M/1 queueing model for communication cost, M/M/n queueing model for computation cost, and a fix value model for storage cost, we formulate the problem of optimal user scheduling to minimize the cost per user in the Multi-Cloud environment. In our proposal solution, we develop a list of potential load paths and choose the optimal one with the MFDL for each of user within the system.

The performance of OSMC algorithm was compared with RR in our experiments. Simulations were carried out on Multi-Cloud with 10 CSPs. Further, we were able to prove that the OSMC is scalable, extensible, and convenient for implementation. In all areas considered, the OSMC outperforms the RR, including cost per user, maximum number of users supportable by the system, resource utilization of CSPs. Our methodology can be applied to other utility cost models, such as learning curve, to satisfy various requirements of different Multi-Cloud. We also find that the order of the user scheduling has no effect on the final cost per user and the OSMC can be easily extended to dynamic situations without pre-defined set of users.

In cloud/edge computing systems, privacy-preserving [20], security [23], etc., are very important. In our future work, we shall address these challenges and consider the corresponding computational cost in our framework.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The co-authors are from I2R Singapore, NUS Singapore, Chongqing Jiaotong University China, and State University of New York USA. The reviewers from the four Universities and Institutes shall have the conflict of interest and cannot review the draft. The domains shall be I2R.a-star.edu.sg, nus.edu.sg, cqjtu.edu.cn, and newpaltz.edu.

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References

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