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COST OPTIMIZATION FOR DISTRIBUTED BIG DATA ANALYTICS

Dr.P.Ananthi
Assistant Professor
Kongu Engineering College, India
ananthiparth@gmail.com

ABSTRACT- The explosive growth of demands on big data processing imposes a heavy burden on computation, storage, and communication in data centers, which hence incurs considerable operational expenditure to data center providers. Therefore, cost minimization has become an emergent issue for the upcoming big data era. As a result, three factors, i.e., task assignment, data placement, and data movement, deeply in the operational expenditure of data centers. In this paper, the cost minimization problem via a joint optimization of these three factors for big data services in geo-distributed data centers considered. To describe the task completion time with the consideration of both data transmission and computation, to propose a 2-D Markov chain and derive the average task completion time in closed-form.

KEY TERMS: Big data, data flow, data placement, distributed data centers, cost optimization, job assignment.

I. INTRODUCTION

Data explosion in recent years leads to a rising demand for big data processing in modern data centers that are usually distributed at different geographic regions, e.g., Google's 13 data centers over 8 countries in 4 continents [1]. Big data analysis has shown its great potential in unearthing valuable insights of data to improve decision-making, minimize risk and develop new products and services. On the other hand, big data has already translated into big price due to its high demand on computation and communication resources [2]. Gartner predicts that by 2015, 71% of world wide data center hardware spending will come from the big data processing, which will surpass $126.2 billion. Therefore, it is imperative to study the cost minimization problem for big data processing in geo-distributed data centers. Many efforts have been made to lower the computation or communication cost of data centers. Data center resizing (DCR) has been proposed to reduce the computation cost by adjusting the number of activated servers via task placement [3]. Based on DCR, some studies have explored the geographical distribution nature of data centers and electricity price heterogeneity to lower the electricity cost [4]_[6]. Big data service frameworks, e.g., [7], comprise a distributed system underneath, which distributes data chunks and their replicas across the data centers for grained load-balancing and high parallel data access performance. To reduce the

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communication cost, a few recent studies make efforts to improve data locality by placing jobs on the servers where the input data reside to avoid remote data loading [7], [8]. Although the above solutions have obtained some positive results, they are far from achieving the cost-efficient big data processing because of the following weaknesses. First, data locality may result in a waste of resources. For example, most computation resource of a server with less popular data may stay idle. The low resource utility further causes more servers to be activated and hence higher operating cost.

II. RELATED WORK

Large-scale data centers have been deployed all over the world providing services to hundreds of thousands of users. According to [11], a data center may consist of large numbers of servers and consume megawatts of power. Millions of dollars on electricity cost have posed a heavy burden on the operating cost to data center providers. Therefore, reducing the electricity cost has received significant attention from both academia and industry [5], [11]_[13]. Among the mechanisms that have been proposed so far for data center energy management, the techniques that attract lots of attention are task placement and DCR. DCR and task placement are usually jointly considered to match the computing requirement. Liu et al. [4] re-examine the same problem by taking network delay into consideration. Fan et al. [12] study power provisioning strategies on how much computing equipment can be safely and effciently hosted within a given power budget. Rao et al. [3]investigate how to reduce electricity cost by routing user requests to geo-distributed data centers with accordingly updated sizes that match the requests. Recently, Gao et al. [14] propose the optimal workload control and balancing by taking account of latency, energy consumption and electricity prices.

III. SYSTEM MODEL

In this section, we introduce the system model.

Network Model

We consider a geo-distributed data center topology as shown in Fig. 1, in which all servers of the same data center (DC) are connected to their local switch, while data centers are connected through switches. There are a set I of data centers, and each data center i 2 I consists of a set Ji of servers that are connected to a switch mi 2 M with a local transmission cost of CL. In general, the transmission cost CR for inter-data center traffic is greater than CL, i.e., $CR > CL$. Without loss of generality, all servers in the network have the same computation resource and storage capacity, both of which are normalized to one unit. We use J to denote the set of all severs,

$$\text{i.e., } J = J_1 \bigcup J_2 \cdots \bigcup J_{|I|}.$$

The whole system can be modeled as a directed graph G D (N; E). The vertex set N D MSJ includes the set M of all switches and the set J of all servers, and E is the directional edge set. All servers are connected to, and only to, their local switch via intra-data center links while the switches are connected via inter-data center links determined by their physical connection. The weight of each link

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$w(u;v)$, representing the corresponding communication cost, can be defined as

$$w^{(u,v)} = \begin{cases} C_R, & \text{if } u, v \in M, \\ C_L, & \text{otherwise.} \end{cases} \quad (1)$$

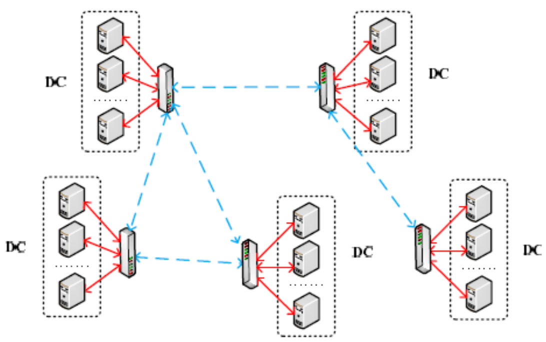

FIGURE 1. Data center topology.

IV. PROBLEM FORMULATION

In this section, we present the constraints of data and task placement, remote data loading, and QoS. Then, we give the complete formulation of the cost minimization problem in a mixed-integer nonlinear programming form.

A. Constraints of Data and Task Placement

We define a binary variable *yjk* to denote whether chunk *k* isplaced on server *j* as follows,

$$y_{jk} = \begin{cases} 1, \text{ if chunk } k \text{ is placed on server } j, \\ 0, \text{ Otherwise.} \end{cases} \quad (2)$$

In the distributed system, we maintain *P* copies for each chunk k^2 *K*, which leads to the following constraint:

$$\sum_{j \in J} y_{jk} = P, \forall k \in K. \quad (3)$$

A server shall be activated if there are data chunks placed onto it or tasks assigned to it.

B. Constraints of Data Loading

Note that when a data chunk *k* is required by a server *j*, it may cause internal and external data transmissions. This routing procedure can be formulated by a model. All the nodes *N* in graph *G*, including the servers and switches, can be divided into three categories:_

Source nodes *u*(*u*2*J*). They are the servers with chunk*k* stored in it. In this case, the total outlet to destination server *j* for chunk *k* from all source nodes shall meet the total chunk requirement per time unit as j_k . Relay nodes m_i(m_i 2 *M*). They receive data from source nodes and forward them according to the routing strategy.

Destination node *j*(*j*2*J*). When the required chunk is not stored in the destination node, i.e., *yjk* D 0, it must receive the data flows of chunk *k* .

Finally, the destination receives all data *k* from others only when it does not hold a copy of chunk *k*, i.e.,y_{ik} D 0. This is guaranteed by (10).

VI. PERFORMANCE EVALUATION

In this section, we present the performance results of our joint-optimization algorithm (``Joint") using the MILP formulation. We also compare it against a separate optimization scheme algorithm (``Non-joint"), which minimum number of servers to be

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activated and the traffic routing scheme using the network flow model.

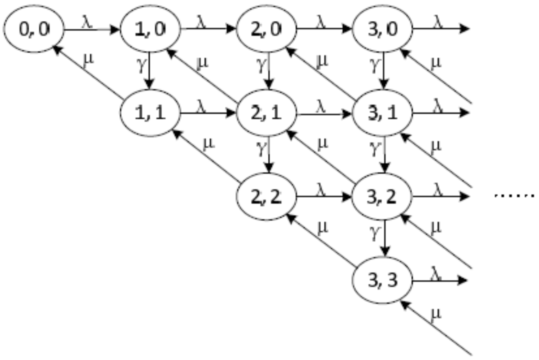

FIGURE 2. Two-dimensional Markov Chain.

In our experiments, we consider j*J*j D 3 data centers, each of which is with the same number of servers. The intra- and inter-data center link communication cost are set as *CL* D 1and *CR* D 4, respectively. The cost *Pj* on each activated server *j* is set to 1. The data size, storage requirement, and task arrival rate are all randomly generated. To solve the MILP problem, commercial solver Gurobi [26] is used.

The default settings in our experiments are as follows: each data center with a size 20, the number of data chunks j*K*j D 10, the task arrival rates *k*2 [0:01; 5]; 8*k* 2 *K*,the number of replicas *P* D 3, the data chunk size k2[0:01; 1]; 8*k* 2 *K*, and *D* D 100. We investigate how various parameters affect the overall computation, communication and overall cost by varying one parameter in each experiment group. Fig. 3 shows the server cost, communication cost and overall cost under different total server numbers varying from 36 to 60. As shown in Fig. 3(a), we can see that the server cost always keep constant on any data center size. As observed from Fig. 3(b), when the total number of servers increases from 36 to 48, the communication costs of both algorithms decrease significantly.

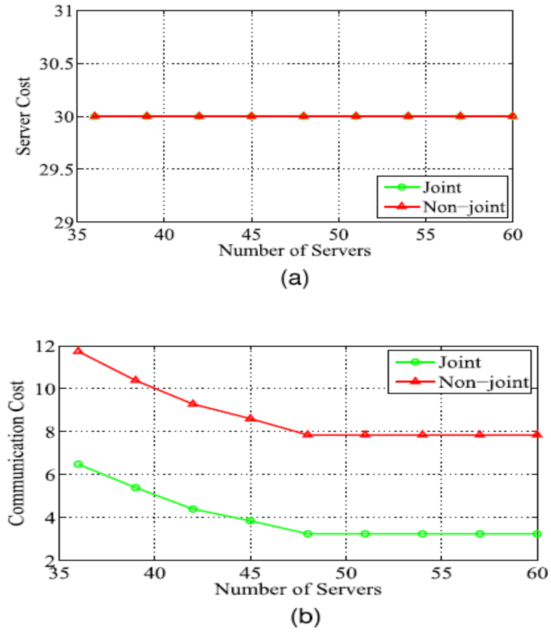

FIGURE 3. On the effect of the number of servers. (a) Server Cost. (b) Communication Cost.

This is because more tasks and data chunks can be placed in the same data center when more servers are provided in each data center. Hence, the communication cost is greatly reduced. However, after the number of server reaching 48, the communication costs of both algorithms converge. The reason is that most tasks and their corresponding data chunks can be placed in the same data center, or even in the same server. Then,

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we investigate how the task arrival rate affects the cost via varying its value from 29:2 to 43:8. The evaluation results are shown in Fig. 4. We first notice that the total cost shows as an increasing function of the task arrival rates in both algorithms. This is because, to process more requests with the guaranteed QoS, more computation resources are needed. This leads to an increasing number of activated servers and hence higher server cost, as shown in Fig. 4(a). An interesting fact noticed from Fig. 4(a) is that ``Joint'' algorithm requires sometimes higher server cost than ``Non-joint''. This is because the first phase of the ``Non-joint'' algorithm greedily tries to lower the server cost. However, ``Joint'' algorithm balances the tradeoff between server cost and communication cost such that it incurs much lower communication cost and thus better results on the overall cost, compared to the ``Non-joint'' algorithm.

VII. CONCLUSION

In this paper, we jointly study the data placement, task assignment, data center resizing and routing to minimize the overall operational cost in large-scale geo-distributed data centers for big data applications. We first characterize the data processing process using a two-dimensional Markov chain and derive the expected completion time in closed-form, based on which the joint optimization is formulated as an MINLP problem. To tackle the high computational complexity of solving our MINLP, Several interesting phenomena are also observed from the experimental results.

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