Optimal Connectivity to Cloud Data Centers

Mirza Mohd Shahriar Maswood, Deep Medhi
University of Missouri–Kansas City, USA
Email: mmnt7@mail.umkc.edu, dmedhi@umkc.edu

***Abstract*—With the increasing dependency of cloud-based services, data centers (DC) have become a popular platform to satisfy customers' requests. Many large network providers now have their own geographically distributed data centers for cloud services, or have partnerships with third party data center providers to route customers' demand. When end customers' requests arrive at a Point-of-Presence (PoP) of a large Internet Service Provider, the provider having DCs in multiple geo-locations needs to decide which DC should serve the request depending on the geo-distance, cost of resources in that DC, availability of the requested resource at that DC, and congestion in the path from the customers' location to that DC. Therefore, an optimal connectivity scheme from the ingress PoP to egress DC is required among the PoPs and DCs to minimize the cost of establishing paths between a PoP and a DC while ensuring load balancing in both the link level and DC level. In this paper, we present a novel mix-integer linear programming (MILP) model for this problem. We show the efficacy of our model through various performance metrics such as average and maximum link utilization, and average number of links used per path.**

***Index Terms*—Cloud Data Centers, Point of Presence, Resource Optimization and Allocation, Load Balancing**

I. Introduction

To satisfy the growing need for cloud-based services such as video streaming, web search, scientific computation, and distributed file system, the size and the number of data centers (DC) are increasing with time. The major cloud service providers like Google, Amazon, and Microsoft have established new data centers throughout the world to offer multiple service regions through geographically distributed data centers to attain a lower cost, lower delay, and higher availability for globally distributed cloud users. For example, Google currently has 9 data centers in the US, 2 in Asia, and 4 in Europe to serve customers throughout the world [1].

Internet Service Providers (ISPs) create a bridge between the customers at the edge and the data centers of the cloud service providers; in some instances, ISPs have their own data centers that are geographically distributed. Typically, a nationwide ISP has Points-of-Presence (PoPs) in every geographic region wherever it has a partnership with a local access provider. Thus, an important problem such an ISP faces is to route requests entering at an egress PoP to a destination DC. The goal of Traffic Engineering (TE) among the PoPs of the ISPs and the data centers is to ensure efficient routing to optimize network and service objectives.

To provide the optimal connectivity from the PoPs to different geo-distributed DCs is a challenging problem for providers. A number of works already addressed how to reduce the intra-DC cost by either better utilizing the server resources or by applying traffic engineering techniques to reduce bandwidth and other operational costs [2], [3]. However, less work has been done to reduce cost, address link congestion and data canter load balancing using traffic engineering techniques for requests between PoPs and DCs.

The novel contribution of this work beyond the state-of-the-art in terms of the optimal provisioning on the cloud environment is our proposed novel optimization MILP-based model to minimize a composite objective that consists of minimizing the routing cost from a PoP to a DC as well as load balancing both at the network level and the DC level. An important point to note here is that we use two types of resources in our approach: network resources (bandwidth) and DC resources. Thus, our model is a unified model on resource optimization between the network and the DC. By conducting a series of systematic studies using different values of the weight factors associated with the composite objective, we present how the average link utilization, maximum link utilization, and the average number of links interplay under different conditions. Furthermore, we use a geographically skewed resources demand generated from one side of the topology to understand how the spatial and temporal diversity of traffic affects the choice of finding the data center that can serve better.

The rest of the paper is organized as follows. The related work is discussed in Section II. In Section III, we present the Problem Formulation. In Section IV, we present the simulation setup and results of our analysis. Finally, in Section V, we summarize our concluding remarks and discuss potential future work.

II. Related Work

Several works have previously addressed reducing delay in the backbone network in a geo-distributed cloud service environment [4], [5], [6]. In [4], an algorithm is proposed to reduce the average delay by assigning the link-distance metric. In [5], the authors proposed an optimization model by addressing the trade-off between survivability and latency in geo-distributed DCs. In [6], an ILP model along with a heuristic is proposed to minimize the traffic on the backbone network by using the best migration sequence among intercommunicating (virtual machines) VMs to schedule the VM migration. Note that our model of reducing link congestion translates to reducing delay.

Some other approaches tried to reduce the cost of providing cloud services by utilizing a spatial and temporal variation of DC maintenance cost and using renewable energy source. In [7], an optimal resource allocation scheme is presented by considering the spatial diversity of the DC cost to satisfy user requirements at a lower cost. A framework is proposed to

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balance the load among Geo-distributed DCs for the requests of web application based on the availability of renewable energy sources on each site. This would reduce the energy consumption cost and brown energy usage by utilizing green energy efficiently [8]. In [9], an optimization model is proposed to minimize the deployment and operational cost for green distributed DCs by reducing the power consumption and server deployment cost.

In [10], a hierarchical approach for workload management in geo-distributed DCs is propoposed to achieve load balancing and energy cost reduction by minimizing the amount of state information exchanged among the DCs. A mixed integer programming is presented in [11] to provision resources for virtual network (VN) requests optimally to maximize the total revenue. In [12], they proposed an optimal route selection technique in a content delivery network (CDN) that enables an edge server to operate within a given region of CDN. This retrieves content from an origin server more effectively by optimally routing through the CDN's own nodes to avoid network congestion. In [13], the authors presented a cooperative mathematical framework on CDN and traffic engineering in an ISP network to reduce the congestion and delay through traffic engineering and optimal server selection technique.

However, we consider the problem from a different and more general point of view where the cloud services are not only limited to web applications or content distribution, but each DC can provide the same service seamlessly. We further consider a two tuple demand of bandwidth and resource requirements to be served both by the network as well as by the DCs. Here, we do not consider the intra-DC (east-west/north-south) traffic, and thus, the detailed internal structure of a DC.

III. Problem Formulation

To depict the problem, consider the topologies shown in Figs. 1 and 2, which depict the Abilene and Agis topologies, respectively. The PoPs are indicated with black dots and the DCs are indicated with red dots. In our model, we assume that ISPs also operate all DCs, and thus, it has full control over both the network and the data centers. While currently in practice, many DCs are provided by independent DC providers, and many large ISPs are starting to have their own DCs so that they can control customers' traffic and revenue in their own network.

In our model, each request consists of 2-tuple $\langle h, r\rangle$ where h is the bandwidth demand of a request and r is the resource demand needed from a DC. Our notion of a request is a collective request, not an individual user's request for the purpose of traffic engineering. Thus, bandwidth demand suits well for this purpose. Certainly, a DC can serve requests from multiple PoPs. We assume that there is a given set of paths P_{ip}^d from PoP i to DC d. The bandwidth request from one PoP to one DC can also be split among available paths from that PoP to that DC in our problem context as discussed later in our formulation. Therefore, the portion of the bandwidth demand that needs to be satisfied by an available path, needs to be satisfied by the capacity of all the links, $c_l, l \in L$ associated with that path $p \in P_{ip}^d$ from a PoP to the DC. The resource request must be satisfied by the capacity of the chosen DC or DCs given by $a_d, d \in D$. Thus, at a particular instant, for a request $q \in Q_i$ from PoP $i \in I$, the request tuple is further represented by $\langle h_{iq}, r_{iq}\rangle$, which is to be served by a DC from the available DCs $d \in D$. Notations used in our model are summarized in Table I.

A. Constraints

Consider an individual request q from PoP i consisting of two tuple $\langle h_{iq}, r_{iq}\rangle$, that is to be satisfied by a data center. This can be indicated through the binary decision variable w_{iq}^d satisfying the following conditions:

$$\sum_{d \in D} w_{iq}^d = 1, \quad q \in Q_i, i \in I \tag{1}$$

That is, just one w_{iq}^d will be 1 for every $q \in Q_i, i \in I$ to indicate the selected data center d. Next, we need to find a single path p for this request from PoP i to this data center. If we indicate the path decision variables by v_{iqp}^d, then selection of a single path is indicated by the following relation

$$\sum_{p \in P_{ip}^d} v_{iqp}^d = w_{iq}^d, \quad q \in Q_i, i \in I \tag{2}$$

When a data center is *not* selected, the corresponding w_{iq}^d is zero, and then for these cases, the above constraint is vacuous.

Since at any instant, there are many requests q from a PoP to a data center, a subset of them will go to a particular DC. In other words, the requests will be spread out among multiple data centers. Thus, from a traffic engineering point of view, we can take an aggregated approach instead of looking at each request individually. This view allows us to sum up all requests from a PoP, i.e., $\sum_{q \in Q_i} h_{iq} = h_i$, $\sum_{q \in Q_i} r_{iq} = r_i$. Secondly, instead of using binary decision variables for each request, we can view the traffic distribution as proportional to different data centers, allowing us to use a real variable to represent the amount of allocation. Therefore, for the rest of the discussion, it suffices to use this aggregated view and consider the problem in terms of a demand request as $\langle h_i, r_i\rangle$ from PoP i, instead

Fig. 1: Abilene Topology

Fig. 2: Agis Topology

TABLE I: Notations used in Formulation

Constants:
D = Set of data centers
I = Set of point of presence (PoP)
Q_i = Set of requests at PoP i
L = Set of links
P_{ip}^d = Set of paths from PoP i to datacenter d
M = A large positive number
ε = A very small positive number
h_{iq} = Bandwidth demand generated by request q at PoP i
r_{iq} = Resource demand generated by request q from PoP i
h_i = Bandwidth demand generated from PoP i
r_i = Resource demand generated from PoP i
c_l = Available capacity on link l
a_d = Capacity of data center d
$\delta_{ipl}^d(t)$ = Link-path indicator: 1 if path p which is set up from PoP i to data center d uses link l in order to satisfy demand of PoP i by data center d, 0 otherwise
α, μ, γ = Weight parameters related to 3 optimization objectives

Variables:
w_{iq}^d = Binary decision variable (0/1) for request q from PoP i to select data center d
v_{iqp}^d = Binary decision variable (0/1) for selecting path p for request q from PoP i to data center d
y_i^d = Bandwidth allocation for traffic from PoP i to data center d
x_{ip}^d = Bandwidth allocation in path p, if traffic from PoP i to data center d uses path p
z_{il}^d = Bandwidth requirement on link l for PoP i to be satisfied by data center d
u = Max. utilization of any link
$\widetilde{z}_{il}^d$ = Binary decision variable to indicate whether link l is used to establish path from PoP i to data center d (this parallels z_{il}^d)
g_i^d = Resource allocation for traffic from PoP i to data center d
$\widetilde{y}_i^d$ = Binary decision variable to indicate that traffic originated from PoP i is served by data center d (this parallels y_i^d)
k_d = Max. utilization of DC d

of $\langle h_{iq}, r_{iq} \rangle$. With this aggregation, the total amount of the bandwidth demand originated by the requests from a particular PoP i is the summation of the bandwidth that is to be allocated from PoP i to all chosen DCs d to satisfy those requests:

$$\sum_{d \in D} y_i^d = h_i, \quad i \in I \tag{3}$$

The bandwidth that is allocated to a particular path from PoP i to DC d is given by using the path flow variables x_{ip}^d:

$$\sum_{p \in P_{ip}^d} x_{ip}^d = y_i^d, \quad i \in I, d \in D \tag{4}$$

If any bandwidth is allocated on particular path p to satisfy a portion of the request of bandwidth demand h_i from any PoP i, then all the links associated with that path have to carry that portion of demand h_i. Therefore, we can determine the flow on each link $l \in L$:

$$\sum_{p \in P_{ip}^d} \delta_{ipl}^d x_{ip}^d = z_{il}^d, \quad l \in L, i \in I, d \in D \tag{5}$$

The total amount of bandwidth required from one link l must not exceed the capacity of that link times the maximum utilization of any link. This constraint is required to ensure link level load balancing.

$$\sum_{i \in I} \sum_{d \in D} z_{il}^d \leq c_l u, \quad l \in L \tag{6}$$

Note that the maximum utilization of any link cannot be more than 1 at any point.

$$u \leq 1. \tag{7}$$

Constraints (8) and (9) are used to identify the links that are used to establish the paths from PoP i to DC d.

$$z_{il}^d \leq M \widetilde{z}_{il}^d, \quad l \in L, i \in I, d \in D \tag{8}$$

$$z_{il}^d \geq \varepsilon \widetilde{z}_{il}^d, \quad l \in L, i \in I, d \in D \tag{9}$$

Now, the total amount of the resource demand originated by the requests from the particular PoP i is the summation of the resources that is allocated to all chosen DCs d to satisfy those requests:

$$\sum_{d \in D} g_i^d = r_i, \quad i \in I \tag{10}$$

Next, we introduce a binary shadow variable $\widetilde{y}_i^d$ corresponding to y_i^d to track one-to-one mapping from PoP i to data center d by using a large positive number M and a small positive number ε. Then, we address resource allocation of g_i^d to the appropriate tuple $\langle i, d \rangle$, ensuring this is in accordance with shadow variable $\widetilde{y}$.

$$y_i^d \leq M \widetilde{y}_i^d, \quad i \in I, d \in D \tag{11}$$

$$y_i^d \geq \varepsilon \widetilde{y}_i^d, \quad i \in I, d \in D \tag{12}$$

$$g_i^d \leq M \widetilde{y}_i^d, \quad i \in I, d \in D \tag{13}$$

$$g_i^d \geq \varepsilon \widetilde{y}_i^d, \quad i \in I, d \in D \tag{14}$$

The resource requirement generated by the requests coming from all PoPs $i \in I$ to data center d must not exceed the available resources of that data center times the maximum utilization of any DC. This constraint is required to ensure DC level load balancing.

$$\sum_{i \in I} g_i^d \leq a_d k_d, \quad d \in D \tag{15}$$

Since the maximum utilization of DC d cannot be more than 1, we have

$$k_d \leq 1, \quad d \in D \tag{16}$$

Note that the advantage of parameter k_d is that our model is applicable to the scenario when the maximum DC utilization for each data center is set to different values than one.

B. Objective Function

We consider three goals: minimize bandwidth cost of routing, minimize the maximum link utilization, and to load balance DC resource utilization. Since these goals are of different types, we take a utility function-based approach by assigning weights to these three components that form the objective function. Different weight parameters, α, μ, γ, allow us to understand the influence of each term on the overall decision. Thus, the objective function can be written as:

$$\min \alpha \sum_{i \in I} \sum_{d \in D} \sum_{l \in L} \widetilde{z}_{il}^d + \mu u + \gamma \sum_{d \in D} k_d. \tag{17}$$

In summary, the goal of the optimization problem is to minimize (17) subject to the constraints (3) - (16).

IV. Simulation Study Setup and Result Analysis

To conduct our study, we used two topologies, Abilene and Agis, shown in Fig. 1 and 2, consisting of a set of PoPs and geo-distributed DCs. The location of these DCs is chosen from Google's current DC locations in the US. We set a maximum number of paths from a PoP to a DC where a bandwidth demand generated from a PoP can be split among all the available paths to reach the chosen DC. We consider the capacity in the directly connected links between a PoP and a DC to be 1000. For all other links, we consider the capacity as 100. Parameter values used for the topologies are summarized in Table II.

To solve the optimization model at any instant, we use an AMPL/CPLEX (v 12.6.0.0) tool environment. For the experiments we conducted, solving the MILP model using CPLEX took a minimum of 0.05 and 0.66 (scenario-1) seconds to a maximum of 1.16 and 67.49 seconds (scenario-3) for Abilene and Agis, respectively, and based on the different conditions set up at different scenarios and amount of bandwidth demand. In most cases, the MILP problem was solved optimally. For the instances when it was not solved optimally, the highest optimality gap for Abilene was observed to be 0.52%, while for Agis, the gap was observed to be 3.39%.

Recall that a request is represented by the tuple $\langle h, r \rangle$. We varied h and r separately for different scenarios as shown in Tables III and IV. For simplicity, we consider the capacity of a data center as a whole that is used to satisfy the resource requirements (r) generated from the PoPs. We used both fixed demand (FD) and lognormal distribution (LD) of the bandwidth requirement generated from PoPs. LD was used since an earlier study found the distribution of traffic to follow a lognormal distribution in wide area networks [14]. We kept the average value of required bandwidth of all PoPs the same for both FD and LD. The standard deviation for LD was 0.885. For each case of LD, we used 5 independent runs and report the results on the average value.

We varied the value of the weight parameters associated with the individual objectives of the composite objective to understand how it affects the system to give an indicator to the cloud service providers about the importance of each individual objective. We divided our study into two major parts, which motivated us to divide the scenario table into two parts (Group-A and B) as well. These studies reflect a number of systematic changes to understand the impact. In Group-A, we wanted to see how the average and maximum link utilization and average number of links used per path change as we uniformly vary the bandwidth demand (h_i), while keeping the resource demand fixed. In Group-B, we wanted to study how the geographically skewed resources generated by the spatial and temporal variation of traffic generation affects the choice of a DC by using the metrics similar to Group-A.

TABLE II: Topology related parameters

Topology Name	Abilene	Agis
Number of PoPs	11	25
Number of Data Centers	3	5
Number of links	17	35
Number of paths from a PoP to a DC	5	10

TABLE III: Scenario Table (Group-A): h varied while $r_i = 40, a_d(Abilene) = 200, a_d(Agis) = 500$

Scenarios	Description	α	μ	γ
Scenario-1	Using nearest DC	0.33	0.33	0.33
Scenario-2	Link level load balancing	0.01	0.98	0.01
Scenario-3	Both link and DC level load balancing (priority given on link level)	0.01	0.745	0.245
Scenario-4	Both link and DC level load balancing with same priority	0.01	0.495	0.495

TABLE IV: Scenario Table (Group-B): geographically skewed Resources r while $h_i(Abilene) = 50, h_i(Agis) = 25$

Scenarios	Description	α	μ	γ
Scenario-5	Both link and DC level load balancing (priority given on link level)	0.01	0.745	0.245
Scenario-6	Both link and DC level load balancing with same priority	0.01	0.495	0.495
Scenario-7	DC level load balancing	0.01	0.01	0.98

In scenario-1, the value of the weight parameters is the same for all the individual objectives. However, the maximum link utilization and maximum DC utilization are always less than one as usage cannot go beyond the maximum available capacity. The value of another objective, which is minimizing the number of links per request, is significantly larger (first objective in the composite objective). So, multiplying these objectives with the same weight factors means that choosing the nearest DC (requires a less number of links in the path from the request generating PoP to that DC) is almost the sole priority.

In scenario-2, the weight factor associated with link level load balancing is very high compared to the other two objectives that indicate that link level load balancing is the main priority while minimizing the number of links used per request is also important. As we mentioned earlier, the value of the first objective is already high, so even though we multiply it with a small value weight factor, it will still have a strong influence in the overall decision. We want to ensure that choosing the nearest DC is always an important factor as the bandwidth cost and link congestion is affected by this.

In scenario-3, we chose the value of the weight parameters in such a way that importance can be given to all three individual objectives. The physical significance of this is that at first, the request from a PoP will try to be served by the nearest DC if the links associated with the path are not over utilized/congested and the request serving DC is not over utilized as well. Here, we give more importance on link level load balancing than DC level load balancing. In scenario-4, we adjusted the value of the weight parameters to give equal importance on both link and DC level load balancing.

Scenarios 5, 6, and 7 ("Group-B") are used to analyze how the choice of request serving DC varies due to geographically

TABLE V: Skewed Resource Requirement from the PoPs (Used in Scenario-5, 6 and 7)

Abilene Topology

r_1	r_2	r_3	r_4	r_5	r_6	r_7	r_8	r_9	r_{10}	r_{11}
90	80	70	20	80	30	30	20	10	5	5

Agis Topology

$r_{1\to5}$	$r_{6\to10}$	$r_{11\to15}$	$r_{16\to18,20,21}$	$r_{19,22\to25}$
100	50	25	20	5

TABLE VI: DC Capacity Used in Scenario 5, 6 and 7

Topology Name	a_1	a_2	a_3	a_4	a_5
Abilene	200	200	400	X	X
Agis	125	250	250	1000	1000

skewed resource requirements with different DC capacities using parameters, resource, and DC capacity as shown in Tables IV, V, and VI, respectively. Note that since there are 3 DCs for Abilene, a_4 and a_5 are not applicable and marked with 'X' in Table VI.

Our motivation for the choice of the values of the parameters presented in our study was to create different scenarios to check how different system metrics vary. While we discuss a number of results using the above parameter values, we have two main postulates. *Postulate-1:* we postulate that when choosing the nearest DC is the prime objective, the average number of links used per path and the average link utilization will be less compared to the situation where more importance is given on load balancing. *Postulate-2:* In case of geographically skewed resources in one region of the topology, the average number of links used per path will continue to increase if we keep increasing the importance on DC level load balancing.

A. Group-A: Average and Maximum Link Utilization

We presented a comparison between scenario-1 and 2 in terms of average and maximum link utilization in Fig. 3 and 4 for Abilene and Agis, respectively. By varying the bandwidth requirement in an increasing order for FD, we can see that the avg. link utilization was lower in scenario-1 compared to scenario-2, while the max. link utilization was higher under a less overloaded condition. However, as the bandwidth demand increases, at some point the value of these metrics became the same for both the scenarios.

The key point to be noted here is that when the bandwidth demand was high, the links associated with the shortest path to the nearest DC did not have enough capacity to support the bandwidth requirement and that is why the requests had to use an alternate path (not shortest path) to reach the chosen DC in scenario-1. For LD, the avg. link utilization was always lower in scenario-1 compared to scenario-2 while the max. link utilization was always higher. So, postulate-1 holds. For scenario-3 and 4, we found a very subtle increment compared to scenario-2 for both metrics, so we did not plot them here.

B. Group-A: Average Number of Links Used per Path

In Fig. 5 and 6, we presented an analysis on how the average number of links used per path varies for Abilene

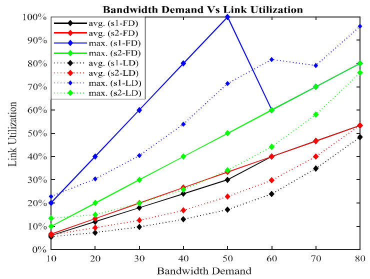

Fig. 3: Link Utilization(Abilene): Scenario-1 vs. Scenario-2

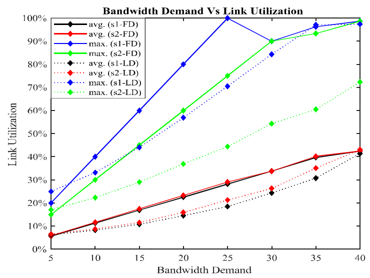

Fig. 4: Link Utilization(Agis): Scenario-1 vs. Scenario-2

and Agis, respectively. For FD, we can see that in scenario-1 where we focus primarily on using the nearest DC, the average number of links used per path increased under an overloaded network condition. Thus, to satisfy the bandwidth demand, it automatically had to use the alternate path. This indicates that the requests were served by the shortest path up to a certain point of bandwidth demand requirement. In scenario-2, when we primarily focused on link level load balancing, the average number of links used per path was higher than in scenario-1 as it was using the alternate path to go to the chosen DC. However, at some point, it merged with scenario-1 (Abilene) for not having enough capacity in the links associated with the shortest path, and it had to choose the alternate path.

Now, we can see that more links have been used per path in scenario-3 compared to 2 and 1, and the highest value of this metric can be seen in scenario-4. From this, we can see that when DC level load balancing gets more influence in the overall decision, the nearest DC is not always chosen. Therefore, the average number of links used per path increased due to choosing the far DC to reach that DC from the request generating PoPs. Similar behavior was found for LD, as the avg. number of links used per path increased gradually from scenario-1 to scenario-4 for the same avg. value of bandwidth requirement. This also indicates that as we increase the weight on load balancing, the avg. number of links used per path increases and therefore, the other part of postulate-1 holds.

C. Group-B: Effect of Geographically Skewed Resources

We created this situation by considering a higher amount of resource requirements (Table V) from the PoPs located near the west coast and increasing the capacity of the DCs (Table VI) located near the east coast of Fig 1 and 2. Then, from scenarios 5 to 7, we continuously increased the value of weight factors associated with DC level load balancing.

As more influence is given on the DC level load balancing, more requests from the west coast were satisfied by the DCs

TABLE VII: Analysis of Geographically Skewed Traffic

Scenarios	Avg. Link Util.(UD)	Max. Link Util.(UD)	Avg. # Links Used per Path(UD)	Avg. Link Util.(LD)	Max. Link Util.(LD)	Avg. # Links Used per Path(LD)
Abilene Topology (Fig. 1)						
Scenario-5	33.38	50.25	2.17	35.50	55.98	2.42
Scenario-6	33.43	50.50	2.33	35.58	56.23	2.46
Scenario-7	56.62	100.00	2.50	59.21	89.85	2.79
Agis Topology (Fig. 2)						
Scenario-5	30.76	74.75	2.77	18.42	42.21	3.06
Scenario-6	34.12	75.25	2.89	20.49	49.06	3.32
Scenario-7	41.92	100.00	3.52	23.56	89.14	3.67

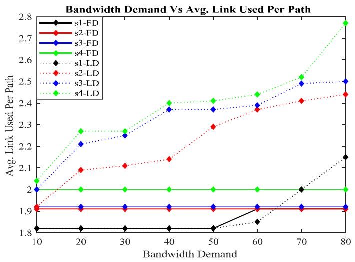

Fig. 5: Average Number of Links Used per Path (Abilene)

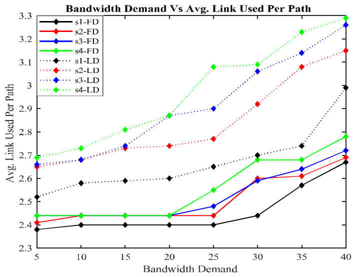

Fig. 6: Average Number of Links Used per Path (Agis)

located near the east coast. We can observe this by looking at the value of average links used per path from Table VII. The value of this metric increased with the increment of weight on DC level load balancing since the more requests will be served by a far DC, then the more links will be required to establish a path to that DC. Therefore, our postulate-2 holds. Furthermore, average and maximum link utilization have also been increased from scenario-5 to 7 as we continue to decrease the weight on link level load balancing. Scenario-7 is the extreme case where most requests are served by the furthest DC, which indicates that our scheme can balance the load among geo-distributed DCs to provide better service to handle geographically skewed resource requirements from DCs.

V. Conclusion and Future Work

Providing the optimal connectivity among the PoPs and DCs while reducing the bandwidth cost, delay and loss is a challenging research problem. In this paper, we present a novel MILP formulation that considers all these issues. It has a composite objective to reduce the bandwidth cost by choosing the nearest DC if the links associated with the path are not congested and the DC is not overloaded. We show the efficacy of our model under both normal and geographically skewed traffic conditions through some metrics e.g. avg. and max. link utilization and the avg. number of links used per path. Our study can help the cloud service providers to better serve their customers based on their requirements.

In the future, we plan to extend our model by considering throughput, latency, and storage as a demand for specific cloud services. We also plan to develop a heuristic so that our scheme can work more efficiently for larger topologies where we can use our optimization model as the benchmark to study the performance of the heuristic.

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