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LOAD BALANCING AND THERMAL-AWARE IN GEO-DISTRIBUTED CLOUD DATA CENTERS BASED ON VLANS

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ABSTRACT:

Power consumption in datacenters has become an emerging concern for the cloud providers. This poses enormous challenges for the programmers to motivate new paradigms to enhance the efficiency of cloud resources through designing innovative energy-aware algorithms. However, balancing the weights over geographically dispersed datacenters has been shown to be essential in decreasing the temperature consumption per datacenter. In this paper, we have formulated a load balancing paradigm to exploit the idea of scheduling scientific workflows over distributed cloud resources to make system outcome more efficient. The proposed heuristic works based on three constraints. First, initiating cloud resource locality for tenants and calculating the shortest distance in order to direct module applications to the closet resources and conserving more bandwidth cost. Second, selecting the most temperature aware datacenters based on geographical climate to maintain electricity cost for the providers. Third, running multiple datacenters within the same geographical location instead of housing the entire workloads in a single datacenter. This allows providers to take a tremendous advantage of sustaining the system from degradation or even unpredictable failure which in turn will frustrate the tenants. Furthermore, applications are formulated as Directed Acyclic Graph (DAG)-structured workflow. For the underlying cloud hardware, our model groups the cloud servers to communicate as if they were in the same physical location. Additionally, both modes, on-demand and reservation, are supported in our algorithm. Finally, the simulation showed that our method was able to enhance the utilization rates about 67% compared to the baseline model.

Keywords—energy efficiency, directed a cyclic graph, workflow

1. INTRODUCTION

Nowadays, Cloud computing systems provide the customers with a virtualized access to the resources that are geographically distributed around the world and offer them both on-demand and reservation mode. However, today modern datacenters require hundreds of thousands of Cloud-based VMs to retrieve the massive scheduled scientific application workflows which require instant data processing. This technique of distributing high dedicated communication bandwidth of cloud datacenters based on diversity helps the providers to satisfy their desires of lowering the risk of system frustrating and meanwhile regulating the electricity bills by re-adjusting the direction of workloads to the most efficient resources. According to a statistic reported by both the Natural Resources Defense Council (NRDC) [1] and the U.S. Environmental Protection Agency (U.S. EPA) [2], just in 60 seconds, 204 million email messages are exchanged, 5 million searches are made on Google engine, 1.8 million "Likes" are generated on Facebook, 350,000 tweets are sent on Twitter, $272,000 of merchandise is sold on Amazon, and 15,000 tracks are downloaded via iTunes. This is based on statistics collected from corporations such as Google, Facebook, Twitter, Amazon, and Apple just in 2013. However, the EPA center reported that even the most modern data centers consumed 61 billion kWh of electricity within one year [3,4]. As these agencies state that unbalanced mapping of scientific application workflows over cloud resources could be a cause of such unacceptable energy waste, equilibrium the weights over these units consider to be one of the most decisive issues facing today's parallel computing system. However, it is the cloud provider's desire to increment their profits and satisfy consumer's requirements through establishing an effective strategy that can guarantee both the availability of data locality and regulate the rates of electricity bills. Since assigned workloads is a function of time, it can be changed over the time of day and day of week, our designation is to present a new vision of designing a paradigm of scheduling scientific workflows over cloud resources within three considerations. First, calculating the shortest distance for the tenants to access cloud resources and direct their modules to these resources based on cloud resources locality. This assists providers to utilize network bandwidth more efficient and decrease the problem of network congestion. Another consideration is to maintain the electricity consumption by datacenters based on geographical climate of the datacenter. This allows providers to send out the modules to the most temperature aware resources within a datacenter. Finally, instead of scheduling the entire workflows to a single datacenter, we have initiated multiple datacenters within the same geographical location. This prevents the system from degradation and unexpected failures which in turn damages all the tenant's requests. This all should be satisfied without degrading the Quality of Service (QoS). However, our module applications are formulated as Directed Acyclic Graph (DAG)-structured workflow and both on-demand and reservation modes are being supported.

2. RELATED WORK

Improving the proportion of resource utilization over cloud infrastructure is the highest priority for cloud providers. These challenges motivate them to come up with some intelligent frameworks that can bargain both the makespan and the energy cost in terms of establishing cloud servers and consuming electricity bills. For decades, many researches have shown that such problematic issues could be addressed and resolved through balancing the workloads over cloud resources in a way that every computing node shares the overloads to turn out the system into more productive prototype. This will in turn assist the providers to boost the module's execution process and meet the consumer's requirements in order to modulate the electricity budget. A framework was proposed for balancing the requests made by consumers in web application based on the availability of renewable energy sources [5]. The Amazon Elastic Compute Cloud (EC2) service model was optimized in [6]. Based on the benchmarks for prototypical scientific applications, the test results was evaluated versus local compute clusters. However, A load-balanced heuristic was developed in [7] to bargain the weights over cloud infrastructure based on Simulated Annealing (SA) to superior First Come First Serve (FCFS), Round Robing, and local search algorithms for instance Stochastic Hill Climbing (SHC) algorithm. This algorithm was applied in [8] to enhance the scheduling process of workloads over executed cloud-based VMs. with advanced virtualization techniques, offline solution alongside online solution plays a critical rule in most researches. A model based on online and offline solution was discussed in [9]. The system initiates with offline solution to determine the placement for module applications based on well-known method namely force-directed scheduling. Then, via online solution the module applications migrate and consolidate to other distributed resources without degrading the QoS. Furthermore, A DVFS temperature aware heuristic was developed in [10] to keep the temperature values at steady level between dual pre-defined thresholds. Load balancing methods was used in [11] to find equilibrium between executing module application and energy consumption in order to increase system throughput.

3. SYSTEM FRAMEWORK AND ANALYTICAL MODEL

3.1 System Framework

To achieve better utilization rate over cloud resources and to be content with consumer's requirements, cloud service providers are highly motivated to structure an intelligent cloud meta-mapper that can balance the scheduling workloads via cloud datacenters with on-demand and pay-on-the-go services which are realized through virtualization technology [2] so that the consumers can access remotely their local resources from different geographical locations and their needs at sensible cost in terms of electricity prices within QoS requirements [12-15]. Fig. 1 explains cloud system architecture.

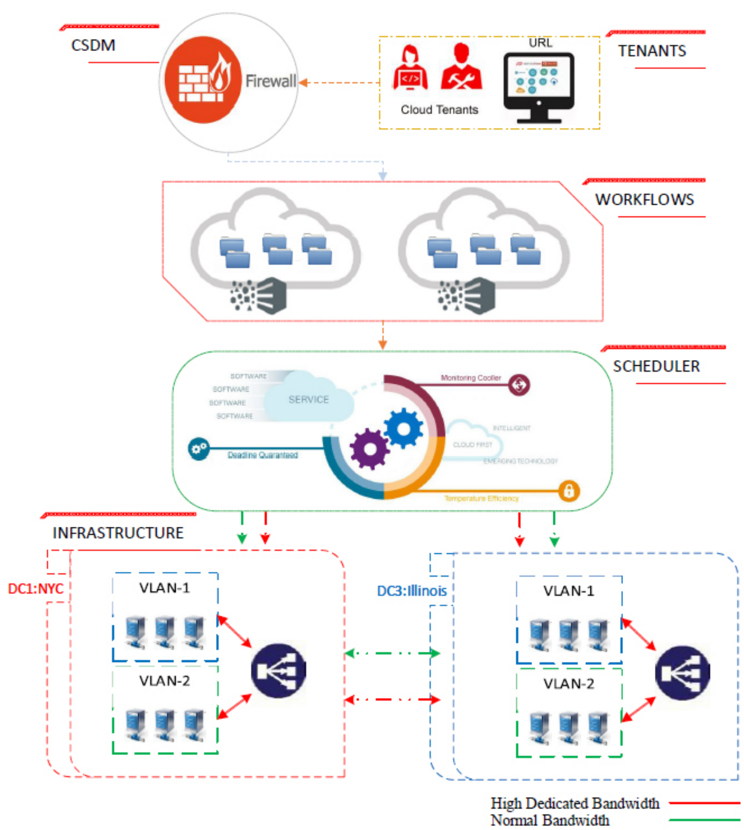

Fig. 1: Cloud System Framework

3.2 Cloud-based Load-Balancing Model

According to previous researches, selecting the optimal equilibrium between workloads and energy consumption increases system throughput and resource utilization [16]. To adjust the energy consumption based on assigned workloads, we first classify the available datacenters based on geographical locations and temperature climate of these datacenters. Then, based on tenant's location, assigned workflows transfer to the closet datacenters to save more bandwidth cost within guarantee Quality of Service (QoS). This also assists providers to avoid network congestion as much as possible. However, these available datacenters might have different temperature climate. Taking electricity cost into consideration, the datacenter that can conserve more electricity bill will be selected. The fact that the electricity cost is a function of time [17] and it is changed based on weather climate, we concentrate on sending the heavier workloads to the datacenters that do not need to initiate more cooling systems. Moreover, we are mainly focusing on scheduling these workloads over these datacenters efficiently to balance both system throughput and energy consumption. To avoid the problem of the system degradation or even unpredictable failure which in turn will frustrate the tenants, we operate multiple datacenters within the same geographical location instead of housing the entire workloads in a single datacenter. The cloud-based load balancing model has been formulated mathematically in equations (1) and (2). However, the major steps of our paradigm is explained in algorithm 1 and the system flowchart is illustrated in figure 2 respectively.

Input: $\mathcal{W}_i$ a workflow $\{\mathcal{W}_1, \mathcal{W}_2, \mathcal{W}_3, \ldots\ldots, \mathcal{W}_m\}$
Input: $\mathcal{DC}_i$ a datacenter $\{\mathcal{DC}_1, \mathcal{DC}_2, \ldots\ldots, \mathcal{DC}_n\}$
Output: balanced scheduled workflows

SET Utilization Rate (UR) to 0
FOR each datacenter in available datacenters

COMPUTE Total electricity consumption cost.

COMPUTE Total bandwidth delay link from the source to the destination.

IF Total > current UR $(\mathcal{W}_i)$ THEN
SELECT the datacenter for $\mathcal{W}_i$
FOR each virtual node in that datacenter

COMPUTE weights over resources
IF system capability > weight
assign $\mathcal{W}_i$ onto virtual node
END IF

END LOOP
ELSE
SKIP datacenter and SELECT next
END IF

RETURN Total in Result

END LOOP

Algorithm 1: Cloud-Based Load Balancing Model

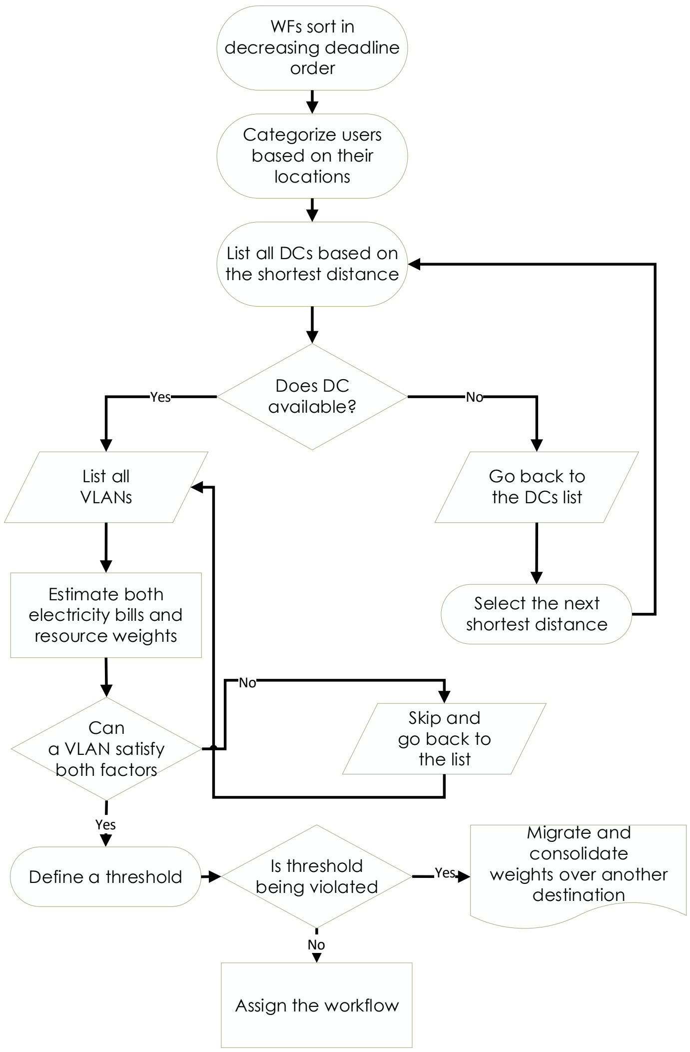

Fig. 2: System Flowchart

$$\mathcal{COST}_{\mathcal{S},\mathcal{L}}^{\mathcal{W}_k,\mathcal{V}} = \min \sum_{\mathcal{VLAN}_{\mathcal{V}} \in \mathcal{DC}_m}^{\mathcal{V}=1} \mathcal{BDL}_{\mathcal{S},\mathcal{L}} + \mathcal{ELC}_{\mathcal{V}} \quad (1)$$

$$S = \begin{cases} \mathcal{VLAN}_{tmp,\mathcal{V}} < \mathcal{UP}_{thr} \ \ and \ > \mathcal{LOW}_{thr} \\ \mathcal{W}eight_{\mathcal{W}_k} < \mathcal{SYS}_{cap,\mathcal{V}} \end{cases}$$

$$\mathcal{ELC}_{\mathcal{V}} = \int_{t_0}^{t_1} (\mathcal{P}_{\mathcal{V}} * \mathcal{R})(t)dt \quad (2)$$

Where $\mathcal{W}_k$ is a workflow k scheduled onto cloud resource $\mathcal{V}$ and $\mathcal{BDL}_{\mathcal{S},\mathcal{L}}$ is the bandwidth delay link from the source to the destination. $\mathcal{ELC}_{\mathcal{V}}$ is the electricity consumption of virtual local area network $\mathcal{V}$. $\mathcal{SYS}_{cap,\mathcal{V}}$ is the system capability of VLAN $\mathcal{V}$. $\mathcal{P}_{\mathcal{V}}$ is the power consumption of VLAN $\mathcal{V}$ and $\mathcal{R}$ is the rate which is measured by dollar sign.

4. CLOUD BASED SCIENTIFIC WORKFLOW MODULE

The reason that we modeled our module applications as scientific workflows is both the dependency and parallelism exist in this framework's features which requires that cloud images distributed over a group of VMs. Although this type of scheduling could be a more problematic and challenging issue, the providers can get the advantage of gaining highest profit through increasing the efficiency of execution process. However, both types of scientific workflow (single module application and DAG-Structured workflow) are configured in this work-simulation; None of the modules can start their execution cycles until they receive the aggregate inputs from preceding tasks which then multiplied by their complexities as formulated in equation (3).

$$\mathcal{R}_{\tau_0,\tau_n}^{\mathcal{W}_m,\mathcal{V}} = \sum_{u_i \in \mathcal{W}_m,\mathcal{V}} \frac{\gamma(u_i) \times \xi(\psi_i)}{\left(\mathcal{C}_{\mathcal{V}\in\mathcal{DC}_m}\right)_{\tau_0,\tau_n}} \quad (3)$$

$$\mathcal{S}ubject\ to:\ u_i \in \mathcal{CP}(\mathcal{W}_i)$$

5. PROBLEM FORMULATION

As our major concern in this experiment is to increase the cloud provider's payoff through mapping the module applications based on consumer's geographical locations, seeking and selecting an appropriate datacenter that can satisfy factors such as balancing weights over execution resources within sensible electricity cost could be a serious problematic. Based on aforementioned facts, we formulae our paradigm's scheduling problem in equation (4) as:

$$\mathcal{SCh}_{\mathcal{VLAN}}^{\mathcal{W}_k} \sum_{\mathcal{CDC}}^{k=1} \sum_{\mathcal{VLAN}}^{m=1} max[\mathcal{PFF}(\mathcal{W}_m)] \quad (4)$$

$$S = \begin{cases} \mathcal{S}atisfy\ \mathcal{W}eight,\ \mathcal{B}alance \\ \mathcal{S}atisfy\ \mathcal{S}hortest\ \mathcal{D}istance \\ \mathcal{S}atisfy\ \mathcal{L}owest\ \mathcal{E}lectricity\ \mathcal{B}ill \end{cases}$$

6. PERFORMANCE EVALUATION

We have simulated 10 different workflows to be dispatched over Cloud-based VMs in 10 different datacenters which are geographically distributed. Two factors to be considered when the paradigm has been programmed via Open Source Java-based CloudSim toolkit. The first one is selecting the shortest distance to the destination based on both virtual local area network and weather climate in these area networks while the second one is related to balancing the weights over cloud resources with take advantage of idle computing nodes. Within these two concerns, the provider can boost the resource utilization rates and do effective oversight of the financial reporting process. However, we compared our algorithm with another one namely "Baseline" algorithm. The last one is based on scheduling cloud module applications over cloud servers without equilibrium consideration. Furthermore, we have simulated 12 different cases to make our outcome more precise. As illustrating and drawing the total of 20 trials is not going to be practical and feasible, a partial of the results with the full coverage of the scenario has been explained. From the 10 datacenters that have been established, we have selected 6 source units based on their According to the plot (4-a), our heuristic balanced the weights over cloud resources more than what baseline algorithm has gained. The value rates over datacenters [1-6] are very close in our method and conserved a tremendous amount of energy due to operate the idle severs to fulfil the equilibrium status with heavy weight resources while the baseline approach has unsteadied balance scale. On the other side, we have scheduled 6 different scientific workflows over two powerful datacenters as shown in fig. (4-b). Each one includes three different VLANs. When the workflows are mapped over VLANs [1-3] from datacenter-3, the two algorithms, our balanced heuristic and baseline one, showed a considerable distinction. The red spot in VLAN-1 shows the idle resource when the module applications are being executed via baseline algorithm while in our algorithm for the VLAN-1, there is still a small portion of idle nodes exist, but the majority are changed to active hosts and shared the resources with heavy weight nodes. For the rest of VLANs, there is no idle resources exist in our algorithm although the case gets worse for the baseline heuristic as shown in fig. (4-b). However, as mentioned before, regulating electricity consumption was one of our problematic issue. In our scheme, we took diversity geographical into account to meet both necessities the user's data locality and electricity adjustment. Same previous scenario, we have scheduled batch of workflows over single datacenter and a per of workflow over batch of cloud datacenters as shown in fig. (5-a) and fig. (5-b) respectively to guesstimate the conclusion. The expenditure of electricity rate in our paradigm was very sensible. The rates were between (24.23 to 56.87$) in the first figure and (15.12 to 37.98$) in the next one. For the baseline heuristic, the rates were imperceivably. The first evaluation recorded the values of (34.56 to 77.89$) while the second one resumed (21.33 to 55.67$). Cloud provider's profit is another constraint that has been adopted to evaluate the effectiveness of the both algorithms. As illustrated in fig. (6-a), after dispatching cloud module applications in scientific workflow-9 over six different datacenters, the load-balanced algorithm achieved better outcome compared to the baseline heuristic. The lowest rate our model resumed was (39.89$) while the highest one was (94.12$). For the baseline algorithm, the minimum was (21.56$) and the maximum was (64.12$). This attainment in our method is because of the equilibrium of assigned weights over cloud-based VMs execution units in per cloud datacenter. Likewise, in fig. (6-b), six different workflows have been scheduled via datacenter-7 with the same evaluation objective. Load-balanced algorithm had the ability to boost the interest to (44.78$) in workflow-4 and (37.89$) in workflow-3. For the baseline model, the tiptop was (34.23$) and (25.56$) in both workflows (3 and 4). Furthermore, in table 1, we have illustrated each of the volume of cloud scientific workflows, the number edges in entire assigned workflows ,geographical locations of cloud datacenters based on datacenter's weather climate, and the volume of available datacenters that can execute cloud module applications. The entire edges that have been applied in our simulation were 1295 edges and the computing nodes that haven operated to execute module applications were 900 nodes in 27 different datacenters. However, the statistical analysis results for the cloud datacenters are explained in table 2 and the statistical analysis results for assigned workflows in table 3.

7. CONCLUSION

Cloud providers are always interested in executing as many modules as possible over less cloud hardware. This increases system throughput and decreases energy consumption by computing servers per datacenter. Efficiently balancing the weights over geographically dispersed datacenters is a critical constraint to achieve the efficiency of system outcome. A load balancing model was proposed in this paper to satisfy three major objectives. First, calculating the shortest distance to the cloud resources so that tenants can direct their module applications to these resources. Second, selecting the most temperature aware datacenters based on geographical climate to maintaining electricity bills. Third, running multiple datacenters within the same geographical location instead of housing the entire workloads in a single datacenter to avoid system degradation or even unpredictable failure which in turn will frustrate the tenant's requests. To evaluate the effectiveness of our heuristic, we compared the algorithm with the baseline algorithm and the results have shown that our paradigm satisfied the aforementioned requirements and enhanced the utilization rates about 67%.

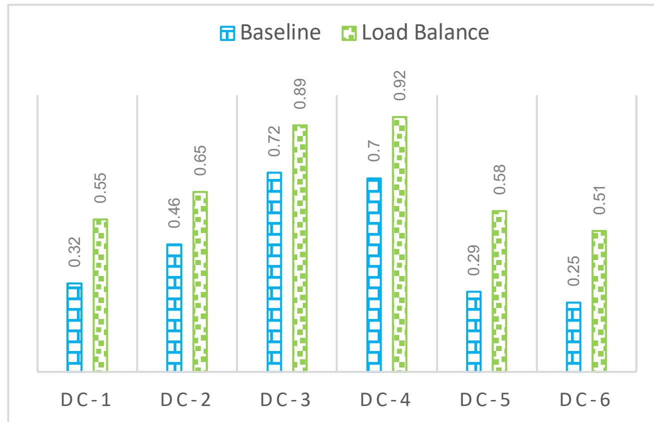

Fig. 3 (a): weight vs datacenters

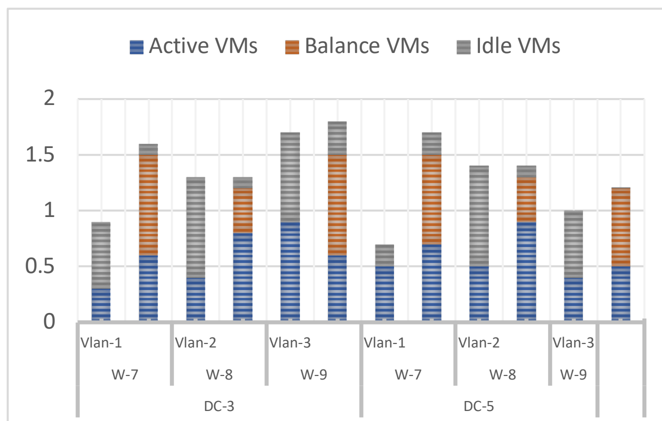

Fig. 3 (b): balanced cloud resources

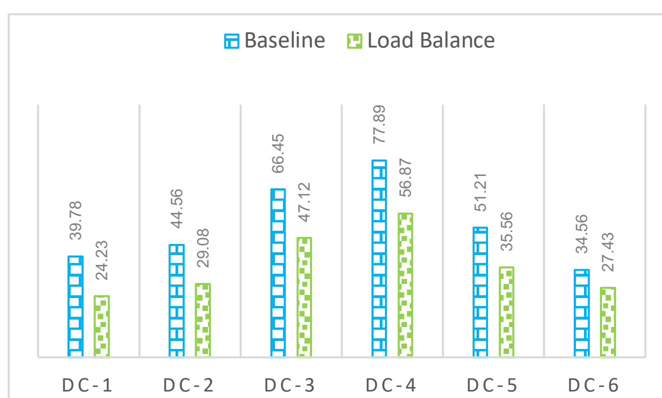

Fig. 4 (a): electricity ($) vs datacenters

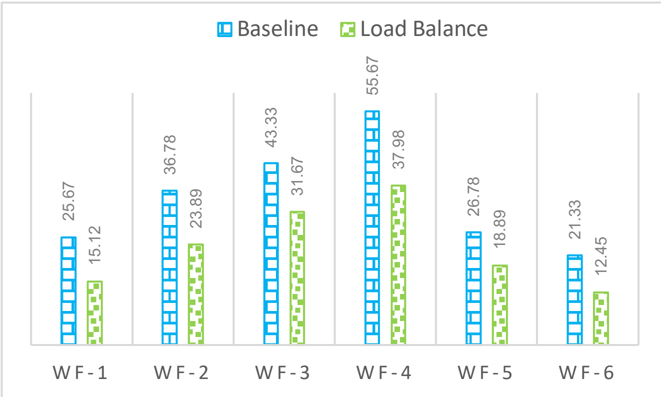

Fig. 4 (b): electricity ($) vs workflows

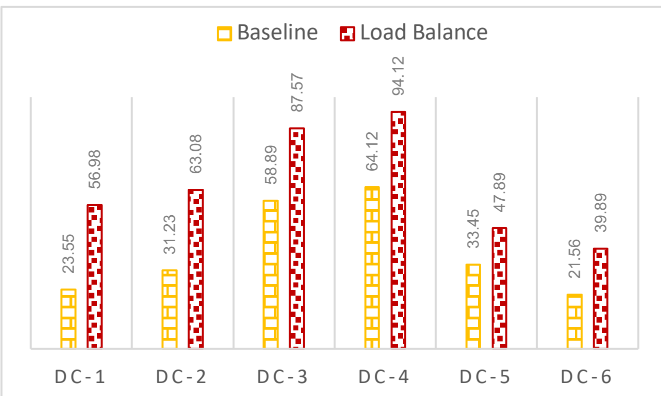

Fig. 5 (a): profit ($) vs datacenters

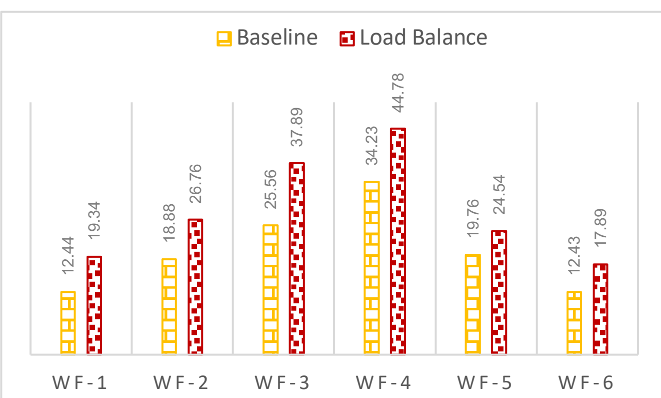

Fig. 5 (b): profit ($) vs workflows

Table 1: Distributed Cloud Datacenters

Workflow ID	**Geographical Location**	**Datacenter Order**
WF -1	Cal., LA., AZ.	DC -7
WF -2	NY., WA., Ph.	DC -3
WF -3	IL., ARK., KY.	DC -8
WF -4	LN., IRL., CE.	DC -2
WF -5	BZ., SW., IR.	DC -4
WF -6	SU., DH., ER.	DC -6
WF -7	ZA., KF., BG.	DC -9
WF -8	ST., TS., NS.	DC -1
WF -9	SO., YT., ST.	DC-5
EDG:1295	**27 DCs**	**900 Nodes**

Table 2: Datacenter Statistical Analysis Result

	UR		**Electricity**		**Profit**	
ID	LBH	BLH	LBH	BLH	LBH	BLH
DC1	0.55	0.32	24.23	39.78	56.98	23.55
DC2	0.65	0.46	29.08	44.56	63.08	31.23
DC3	0.89	0.72	47.12	66.45	87.56	58.89
DC4	0.92	0.70	56.87	77.89	94.12	64.12
DC5	0.58	0.29	35.56	51.21	47.89	33.45
DC6	0.51	0.25	27.43	34.56	39.89	21.56

Table 3: Workflow Statistical Analysis Result

Workflow ID	WF-1		WF-2		WF-3		WF-4		WF-5		WF-6	
Algorithm	LBH	BLH	LBH	BLH	LBH	BLH	LBH	BLH	LBH	BLH	LBH	BLH
Electricity Cost	15.12	25.67	23.89	36.78	31.67	43.33	37.98	55.67	18.89	26.78	12.45	21.33
Provider Profit	19.34	12.44	26.76	18.88	37.89	25.56	44.78	34.23	24.54	19.76	17.89	12.43

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