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Economic-Driven Strategies for Virtual Machine Allocation in Cloud Data Center

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ABSTRACT: In the cloud environment, applications have different requirements and priorities. These applications require the dynamic provision of resources into different types of virtual machines based on the priority requirements. In general, fixed price model is used for allocating the virtual machine to an end-user that may not support an optimal or economic-driven allocation. In this paper, we describe economic-driven techniques for VM allocation and classified these techniques based on specific characteristics required by VM in the cloud. We introduce technical debt as a novel approach for VM allocation and maps the concept of technical debt into the context of VM allocation. Furthermore, we discuss some critical situations that incurred technical debt while operating VMs in the cloud data center.

Keywords: Virtual Machine, Dynamic Allocation, Cloud Computing, Economic Strategies, SLA, Computing Resources, Technical Debt

I. INTRODUCTION

Cloud computing is an on-demand and dynamically scalable computing platform that provides network-enabled resources such as storage, servers, networks, databases, and software services, etc. However, modern computing platform fosters the economically driven service model while delivering these resources in the cloud market. In the cloud environment, several Virtual Machines (VMs) with varying capacity could be instantiated on-demand by a Physical Machine (PM). For optimizing a VM essential network characteristic such as bandwidth and latency required for communication between VMs may lead to communication cost and significant delays [1-2]. Besides Service Level Agreement (SLA) and Quality of Service(QoS), but some other parameters for VM allocation have already been considered in earlier studies including energy consumption, performance, minimize execution time, cost reduction, load balancing, network delays, congestion, and service downtime [3,4, 20].

In cloud environment, each application has different requirements or resource priorities for performing time-dependent tasks. Such application requires dynamic provisioning of resources while instantiating a VM. Moreover, applications are developed and deployed on the multi-tenant architecture which facilitates Shared Resouces as a Service (SRaaS). In this architecture pattern, several users can share the same resource instance on different levels such as application, databases, and VM, etc. For example, several users are participating in a globally accessedSaaS survey application. Since SaaS applications have multi-tenancy in nature and hosted on different VMs located on different locations that require communication among them. In this case, network bandwidth scarcity is a major factor for VM allocation. Also, VMs communication cost influences overall performance. Further, we may consider a situation where a request has been made for a large capacity VM but service provider fails to provide it immediately just because of currently available individual VMs can not fulfill the required capacity. In this situation, we may approach for joint VM provisioning or server consolidation. Moreover, a VM is allocated based on job characteristics. For each job, a different kind of strategy may be implemented for VM allocation. For example, profit and response time are key parameters for utility-based applications; QoS, throughput, and response time parameters are required for SLA based applications.In literature, several research studies have shown that most of the VMs in data cloud center severely under-utilized because of over-provisioning under peak demand that affects the revenue and make the operating environment sub-optimal from VM execution point of view [7-9]. In general,both cases, under-utilization or over-utilization leads the problem of sub-optimal utilization of a VM capacity.A Virtual Machine leads the debt whenever operated sub-optimally in the cloud environment and reasons could be the strategic, managerial, or even unintentional.For addressing these problems, we propose a technical debt approach for VM allocation in the Cloud.

Technical debt could be the results of non-strategic or inappropriate engineering decisions that affect the utility of underlying computing resources and leads sub-optimal utilization of VM in the cloud data center. Besides, VM could be inevitably operated under dynamic changes in requests workload generated by several users in the cloud environment, and consequently, encounter the problem of under/over-utilization of VM; for example, VM under-utilization could be linked with a situation where VM provides more computing resources than the demands of users and going into debt as the cost of unused resources over the underlying VM. In this case, technical debt denotes the cost of engineering efforts required for maintaining optimal utilization of VM plus accrued interest over the technical debt. On the other hand, VM over-utilization could be the consequences of a high volume of requests received on the VM and in response; VM would not be able to process all incoming requests in defined response time and tends to violate the end-users SLA. Here, the cost of penalty generated against each request violation could be count as interest over the technical debt which is incurred unintentionally due to uncertainty in requests workload [10].

The main contribution of this paper is to introduce a novel "Technical Debt" approach for VM allocation. The remaining sections of this paper are organized as follows. Section II introduces essential parameters that could be taken into consideration for VM allocation. Section III describes VM allocation techniques based on the economic driven models and also classified these approaches based on the economic driven parameters. Section IV presents our Technical Debt approach as a novel economic-driven parameter for VM allocation. Furthermore, we illustrate scenarios where TD may be applied for VM allocation. Section V concludes the work.

II. PARAMETERS FOR VIRTUAL MACHINE ALLOCATION

Virtual machine allocation refers to allocating a configuration satisfying the end-user requirements that depend upon resource requirements. The capacity of a VM is usually measured by the number of cores; computing capacity per core; RAM size; and other resources shared by CPU on a given PM. Problems associated with VM allocation are: current availability of number of VMs onto PMs; based on the current workload is there any to add extra VMs or to remove existing ones based on the current workload; the capacity of a PM considered according to various resources like computing capacity, storage, network communication, etc.; a number of resource requirements of a VM may vary over time; VM incurs monetary cost; consumes power that depends on how VMs used; live migration create extra load on PMs and networks; unmatched QoS parameters may result in a penalty [40]. Besides VM configuration, thermal management, some essential parameters must be taken into considerations while allocating a VM to end-user is being discussed in the following section.

A. Service Level Agreement

The workload on each VM must be within its capacity. An overloaded VM, on the other hand, may lead to an SLA violation [1]. SLA includes different kinds of requirements for VM allocation specified as QoS parameters, obligations, and penalties in case of agreement violations [11]. The foundation of SLA is actually the trust in the service provider and its purpose is to ensure that the performance and availability of the VM the service provider guarantees to deliver to the customer. SLA contains service level objectives (SLOs) that include several QoS Parameters like billing, penalties, quality, response time, throughput, etc., let's say availability of a VM is 99.97%; throughput of a VM at peak load is 0.873, are some examples of SLOs, which are objectively measurable conditions for the service. Low-level resource metrics like uptime, downtime, out bytes, in bytes, and packet size are considered as key performance indicators (KPIs). Multiple KPIs are aggregated, composed, or converted to for high-level SLOs. SLAs and SLOs are the basis for service provider selection. Thus, SLAs specify execution time, cost of execution, responsiveness, availability, billing, and jitter for VM.

B. Load Balancing

Load Balancing manages requests by splitting current workload among numerous VMs according to their capacity in such a way that none of the VMs onto PMs remains idle. There must be a zero-downtime solution for every VM. In the context of VM allocation, load balancing is responsible for response time optimization, throughput, VM live migration time, overhead, dynamic scalability, and overall performance, etc. [6].

C. Quality of Service

Uncertainty of the cloud may obstruct the performance of a Virtual Machine. In the context of virtual machine allocation,QoS is actually a broad concept that encompasses different issues such as budget constraints, deadline, response time, availability, and accountability of the overall infrastructure [12]. Different QoS policies are required for different types of applications running on virtual machine. For example, real-time applications need strict policies rather than ordinary policies for low priority applications.

D. Workload

The workload is the number of requests that the VM has been given to process at a given time. A core requirement for VM is workload management that varies over short and long timescales. It models for peak and normal hours of the day. The workload on VMs must be dynamically adjusted to ensure that each VM gets the capacity it needs [13-14].

III. ECONOMIC DRIVEN STRATEGIES FOR VIRTUAL MACHINE ALLOCATION

Cloud computing may be considered as a business package, where users access required services over the internet and pay as per consumption without requiring knowledge about location and management of VMs. An economic driven-strategies may be the result of considering VM allocation based on limited VM capacity that may not be increased or decreased immediately due to certain limitations over the infrastructure. Whenever a cloud user requests for a VM, the cloud data center schedules the Virtual Machines by placing them onto Physical Machines [15]. Researchers have investigated different approaches for optimizing VM or other resources in the cloud data center [3][5][6][11][12]. Maximum utilization of VM resources is the utmost goal of any resource management system and maximum revenue can only be generated when an appropriate strategy has been implemented. A number of studies have already been done on various strategies for reducing cost, energy, response time while considering QoS parameters. Strategies, as discussed in table-1, have been categorized according to energy-aware, evolutionary-based and budget-constraint approaches.

A. Energy-Aware Strategies

Chimakurthi *et al.* [16] proposed a power-efficient resource allocation framework, based on Ant colony that allocates resources to applications without violating SLAs. Qian *et al.* [17] solved two resource management problems first proposed an approach to minimize server operational costs and second resource allocation while considering QoE. Beloglazov *et al.* [18] proposed an energy-efficient system that reduces operational and ensures necessary QoS parameters.Chen *et al.* [19] presented an approach for minimizing the operation cost, server energy consumption while meeting SLAs. Zhang *et al.* [20] proposed a resource allocation algorithm which is based on fair scheduling and energy-aware policy, which reduces energy consumption and increase performance. Chen *et al.* [21] proposed a VM allocation mechanism that reduces the number of PMs and also increases energy efficiency and resource utilization.

B. Evolutionary-Based Strategies

Xiao *et al.* [22] introduced a skewness algorithm that combines different types of workloads and improves resource utilization. Wei *et al.* [23] introduces an evolutionary approach for solving NP-hard scheduling problems. Also presented a game-theoretic method for scheduling dependent services having time and cost-constrained. Ferdaus *et al.* [24] proposed an Ant Colony Optimization mechanism based on meta-heuristic that addresses issues like power consumption and resource wastage minimization. Approach for maximum resource utilization and consolidation have also been presented. Based on ant colony optimization, Liu *et al.* [25] proposed an algorithm to reduce the number of servers being used in cloud data centers**.** For VM allocation, Joseph *et al.* [26] proposed an approach for reducing energy consumption and VM migrations. This approach is based on genetic algorithm.

C. Budget-Constraint Strategies

Mehta *et al.* [27] recommended a dynamic server consolidation framework called ReCon that analyzes resource consumption and reduces the number of servers. Sotomayor *et al.* [28] proposed an architecture that allows cost-effective on-demand short term virtual machine lease management while continuing to support existing workload. Huu *et al.* [29] proposed a cost-based approach for allocatingvirtual resources to workflow-based applications**.** Lee *et al.* [30] considered infrastructure vendors, service providers, and consumers as three-tier cloud structure and addressed the problem of profit-driven service request scheduling algorithm.Entrialgo *et al.* [31] introduces MALLOOVIA, an economically VM allocation strategy for optimizing deployment costs. Zhu *et al.* [32] proposed architecture ensure maximum utilization of virtual resourceswhile reducing cost. Li *et al.* [33] proposed a novel and reliable multicast approach for cloud data center networks that minimize packet loss. Farahnakian *et al.* [34] proposed an architecture in which based on the current resource requirements multi-agent helps to minimize the number of used PMs. Meng *et al.* [35] proposed a VM consolidation approach, in which based on users requirements an aggregated capacity is estimatedand then VM provisioning started.The benefit of this approach is that the idle resources of low utilized Virtual Machine may be borrowed by currently overloaded VMs. This makes possible of maximum utilization of VMs or other resources of cloud infrastructure. Kumar *et al.* [36] introduced a demand-driven preferential resource allocation technique that shows a performance benefit in terms of revenue to the service provider. Lin *et al.* [37] proposed a threshold-based dynamic resource allocation scheme that improves resource utilization and also reduces user usage cost. Schulte *et al.* [38] presented Vienna platform, an integrated approach that combinesthe functionalities of a BPMS with cloud resource management system which reduces cost and time.

Table 1: Economic-Driven Techniques.

Authors	Proposed Approach	QoS Parameters Considered
Chimakurthi *et al.* [16]	Energy-efficient mechanism	Throughput, Response time
Qian *et al.* [17]	Energy efficiency	Cost, Dynamic Voltage
Beloglazov *et al.* [18]	Energy-aware resource management system	Operational Cost
Y. Chen *et al.* [19]	Energy-aware	Cost, Energy
S. Zhang *et al.* [20]	fair scheduling policy and energy-aware policy	Cost, Energy, Performance
L. Chen *et al.* [21]	spatial/temporal-awareness approach	Cost, Energy
Z. Xiao *et al.* [22]	Skewness algorithm	Energy
Wei *et al.* [23]	Evolutionary mechanism	Cost, time
Ferdaus *et al.* [24]	Ant Colony Optimization	Power consumption
Liu *et al.* [25]	Ant Colony Optimization	Cost
Joseph *et al.* [26]	Genetic Algorithm	Cost, time, Energy
S. Mehta *et al.* [27]	ReCon Framework	Cost
Sotomayor *et al.* [28]	Batch Processing/Cost-effective VM lease management	Throughput, Running time
Tram Truong Huu [29]	Cost-based approach	Cost
Lee *et al.* [30]	Pricing model	Cost, Response time
Entrialgo *et al.* [31]	Cost-based approach	Cost, Performance
Zhu *et al.* [32]	Dynamic provisioning technique for shared data centers	Cost
Li *et al.* [33]	RDCM a multicast approach	Throughput
Farahnakian *et al.* [34]	Hierarchical agent-based architecture	Cost, Energy
Meng *et al.* [35]	Joint VM provisioning approach	Performance constraint
N. Kumar *et al.* [36]	Demand based preferential resource allocation technique	Cost
W. Lin *et al.* [37]	Threshold-based dynamic resource allocation	Cost
S. Schulte *et al.* [38]	Vienna Platform	Cost, Time

IV. TECHNICAL DEBT APPROACH FOR VIRTUAL MACHINE ALLOCATION

Technical debt can be attributed to sub-optimal decisions, shortcut on decisions, and/or deferred activities that can incur extra cost/rework if it would be carried in the future as when compared the current time [10]. The major aspect of technical debt is that it must be serviced i.e., once a VM incurs a debt then interest charges must be paid off. The implication of the technical debt is that decision-maker may incur it intentionally but it can't be tracked in a visible way.So a mechanism should be developed to track these invisible debts, For example, using credit card an individual might shop numerous daily usage things which individually costs very less but when being paid at the end of the month the total bill surprised with a huge amount [39]. Moreover, in the recent years, Technical Debt (TD) has been investigated in the field of software engineering, where researchers viewed it from different perspectives such as software architecture, design, testing, coding, requirement, and documentation, etc.

Moreover, we look at the technical debt in the context of VM from different perspectives and classified it as shown in Fig. 1. For example, the first kind of debt is an unintentional debt which may be incurred in a situation where a VM is being allocated to a user without testing for critical conditions that may adversely affect the performance of VM. The second kind of technical debt is that maybe incurred intentionally or strategically [10]. Intentional debt may commonly occur when a conscious decision has been made to optimize the VM performance for the present and do not bother for the future. For example, a decision like “right now, we don’t have time to create another VM on the same PM, so, for the time being, we are just adding a VM which is currently residing in another PM and shall migrate this VM to the original PM later”. Furthermore, intentional debt may be categorized as short term and long term debt. Short-term debt incurred when a vendor has money but does not have it now and is expected to be paid off at regular time intervals. On the other hand, long-term debt has always been taken proactively or strategically, like savings are being used for the expansion of data center and purchasing new IT resources for the same rather than paying the debt. This increase the capacity of the data center to achieve new business targets for generating revenue in the near future [39]. Short term debt may further be divided into focused short term and unfocused short term debt. In the focused short-term debt, an identifiable short cut is taken individually. Let’s say, a bank loan has to be repaid by a data center within a given period of time.Unfocused short-term debt, on the other hand, introduces various micro short cuts that need to be taken into consideration.

Technical Debt may be taken into consideration at Configuration level: let us consider a scenario where a VM is allocated to end-users according to their requirements. An unintentional debt may be incurred because of the compatibility of various resources (e.g. number of CPU cores, cache, storage, bandwidth, etc.) that has not been tested rigorously for critical conditions; Managerial level: as a strategic decision, an intentional debt may be introduced for a short period of time. This debt may be compensated with the future generated revenue. Further, a debt may be categorized as good debt or bad debt. Good debt may be introduced strategically or intentionally, that may be repaid in the future. While a bad debt, maybe introduced unintentionally that cannot be compensated or repaid in the future.

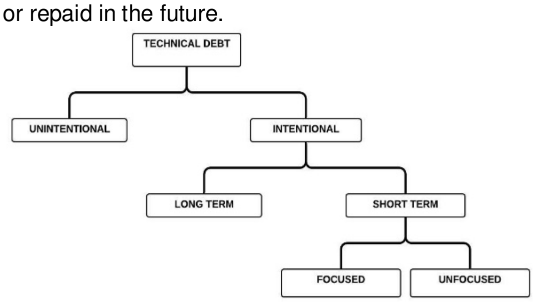

Fig. 1. Types of Technical Debt.

To elaborate Technical Debt in VM allocation, we argue that not necessarily a VM is constantly occupied by users according to its pre-defined capacity. Let’s assume the processing capacity of a VM is 10,000 requests/second. Since the cloud is dynamic in nature, the arrival rate of requests, i.e. the workload, on VM may vary. For example, at time interval t1, the current workload, let’s say 12000 requests/second, is higher than the underlying VM capacity, as a result, it degrades the performance of VM and violates SLA also. But, at t2 time, the workload may be lesser, let’s say 7000 requests/second than the VM capacity and the revenue outweighs its operational cost. As a result, it carried the technical debt. Further at certain t3 time, if more users join the VM, the revenue generated by underlying VM covers previous stage debt [4]. At this stage, it is necessary to consider an economically driven decision in allocation or reallocation for Virtual Machine.

V. CONCLUSION

In this paper, we described different types of economic driven techniques for VM allocation in the cloud data center. We highlighted several potential key parameters to be considered while allocating a VM to end-user. Furthermore, we classified these strategies based on the different allocation parameters, domain constraints and methods such as energy-aware, evolutionary and budget constraint etc. Besides, we introduced the technical debt metaphor as a novel approach for VM allocation and provided a systematic connection that shows how technical Debt metaphor could be applied in the VM allocation domain. We presented several potential cases where technical debt would be incurred and negatively effects the VM utility.

VI. FUTURE WORK

In future work, we will propose a technical debt driven economic model for allocating VM. This model continuously monitors and evaluates the technical debt in VM operating environment. These two activities will facilitates more insight information about technical debt driven economic decision for VM allocation in cloud data center.

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