Tossing *NoSQL*–Databases out to Public Clouds

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***Abstract*—Cloud-Service Providers (*CSPs*) can now handle heavy workloads by occasionally renting resources from *public* clouds. The capabilities and respective lease prices of such infrastructure may significantly vary over time. In this environment, two distinct types of *SLAs* have to work in tandem: *a)* the *SLA* furnished by the *private cloud* to the end user of the application (or database), and *b)* the *SLA* offered by the *public cloud* to the application through its host *private cloud*. This dual and continuously evolving relationship inherently complicates the computation of the operation of cloud applications. In this paper, we present a cost-aware resource provisioning algorithm for *NoSQL*-databases that aims to meet Quality of Service (*QoS*) requirements while minimizing the total cost incurred by its deployment on multiple cloud tiers. Our method is based on look-ahead optimization and takes into account the costs incurred by potential database transitions to new configurations in a heterogeneous multi-cloud environment. Experimentation with a prototype shows that our approach reflects the total cost of a cloud application more accurately than the conventional technique of minimizing *SLA* violations. More importantly, it avoids thrashing of resources.**

***Keywords*—resource provisioning; *NoSQL*–databases; look-ahead optimization**

I. Introduction

Cloud-Service Providers (*CSPs*) dynamically offer computational and storage resources so that users can experience timely execution of their applications regardless of the load and queued jobs the infrastructure has to handle [1]. *CSPs* have the freedom to calibrate both type and number of allotted resources at different points in time so that incoming workloads are successfully handled. In such settings, *QoS* guarantees regarding performance aspects such as response time, throughput, and service availability can be provided to both user applications and launched databases through the use of *SLAs*. When *SLA* violations occur, monetary penalties are accrued for the *CSP* directly affecting not only its revenue but more importantly, its reputation [2].

Untimely provisioning by a *CSP* of its own *internal* (or *private*) resources can lead to depressed leasing costs that ultimately prevent application *QoS*-requirements from being met. Resources needed by an application might change either periodically (i.e., high peak hours or days) or irregularly (i.e., flash crowds that cause sudden, significant depletion of resources). A *CSP* could address internal resource shortages by soliciting additional resources that are available just-in-time from external or *public CSPs*. Dynamic allocation/deallocation of cloud resources might help, but frequent workload changes may lead to deployment thrashing as overheads incurred by the additions/removals of resources may outweigh any short-term benefits gained. To complicate matters further, pricing for leasing equivalent resources from *public CSPs* continuously fluctuates. The latter has to be taken into consideration to identify a resource allocation with minimum cost. It becomes evident that resource allocation is not a straightforward task and so it has recently attracted considerable attention [3]–[5]. In this paper, we investigate the problem of provisioning a popular class of cloud applications collectively known as *NoSQL*-databases [6], [7]. Their key characteristic is that they can scale their performance as they offer horizontal partitioning of data in a shared-nothing fashion through sharding [8].

NoSQL-databases are typically designed to provide availability and fault tolerance by replicating their data multiple times on different nodes across *Gbps*-interconnected *cluster(s)*. The notion of cluster here is that of a set of network-connected machines possibly having different hardware features. As nodes arrive at or depart from the cluster, (e.g., because of energy concerns), replicas have to be expanded or contracted respectively so that availability remains intact. Such "transitions" however expend computational, storage, and network resources and thus, do not occur instantly. This is a key aspect that one has to consider when it comes to *NoSQL*-database provisioning and possibly soliciting resources from external or *public CSPs*.

We present a resource provisioning approach that exploits the pricing models of available resources as well as the costs imposed by potential movements of shards. We aim to minimize the total cost of running a cloud application by using *look-ahead optimization* for a limited time-window. Fig. 1 depicts the key aspects of our approach. The *private CSP* delegates the selection of resources needed to run an application to the provisioning algorithm based on *look-ahead optimization* that oversees the minimization of the total cost. As a result, parts of the database may be "tossed out" to *public CSPs* to expedite processing. Our approach has two phases: the first phase consists of profiling the application so that a performance model for its execution in a specific sample of *cluster configurations* is built; a cluster configuration consists of a specific combination of machines that form a cluster. Several executions of the application on different cluster configurations are needed to stress the application and build a respective performance model. The performance model is required to estimate the behavior of the application on future cluster configurations. Although the creation of a performance model is a costly task in terms of time, it is carried out just once. The second phase requires the following pieces of information (Fig. 1): *i*) the derived performance model, *ii*) the

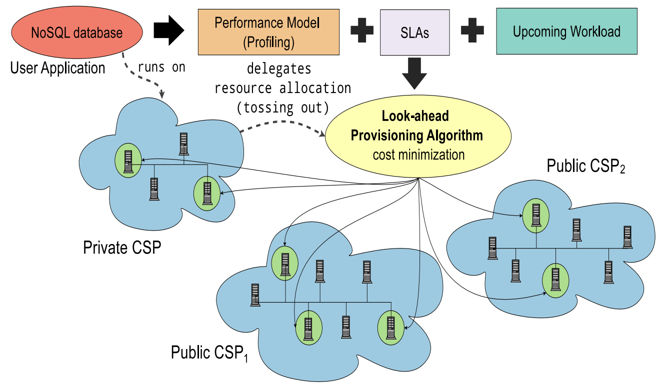


Fig. 1: Our approach considers application profiling, *SLAs*, and hints on upcoming workload to potentially "toss out" portions of *NoSQL*-database(s) to resources from *public CSPs*.

application *SLAs*, *iii*) the prediction of the upcoming workload, and *iv*) the available resources from the *private* and/or *public CSPs*. Using the above information, the resource provisioning algorithm designates which of the available resources should be either added or dropped so that the cost of operating the *private CSP* remains at a minimum.

We make the following contributions:

1) We expose key factors that should be considered in provisioning as they affect the *private CSP* cost either directly or indirectly. We develop a comprehensive cost model to account for all expenses involved including penalties that have to be "paid back" by *public CSPs* should they violate their own *SLAs*. We also introduce the *transition cost* needed to re-host a portion of an application and examine how this affects the total cost through experiments.
2) We address the *NoSQL*-databases provisioning problem taking into account the perspective of the *private CSP* hosting database shards. Thus, we focus on minimizing the *private CSP*'s cost and compare this with the widely-accepted approach of reducing penalties incurred by *SLA* violations.
3) We introduce a look-ahead optimization–based provisioning approach and investigate its effectiveness in comparison with competing approaches including resource thrashing avoidance [4], [9].

The paper is organized as follows: Section II, outlines the salient factors that affect the provisioning problem. Section III discusses both our profiling and the techniques we use to create a predictive model for the cluster. Section IV presents our look-ahead provisioning algorithm and Section V presents key experimental results. Finally, Sections VI and VII respectively describe related work and concluding remarks.

II. Factors in Cloud Provisioning

We outline key factors that should be considered while provisioning for *NoSQL*-databases in the *private/public CSP* context.

A. Opportunistic Use of Public Cloud

When *private CSPs* rent additional machines from *public CSPs* to auto-scale *NoSQL*-databases, they form "clusters" of virtual infrastructures that go beyond what they have available locally. This may transparently offer substantial benefits to users as they see their applications "grow" without necessitating the purchase of new machinery but only the occasional leasing of resources. This leasing highly depends on *i*) the specification of the machine(s) needed, and *ii*) the *SLA* that the *public CSP* offers for the request. Differences between nodes that belong to *public* clouds and nodes in a *private CSP* include the following: *1*) *public CSP* nodes have a rental/lease cost while *private* nodes have an operational cost that entails both energy and maintenance costs, and *2*) a *public* cloud has to compensate the *private* cloud in the form of monetary penalty or *pay-back* anytime an *SLA* is violated. Imposed penalties on *public CSPs* indirectly affect the cost calculation that a *NoSQL*-database host has to pay to a user should *SLA* violations be certified. Thus, the entire amount of penalty is *not* exclusively paid out by the *private CSP* running an application. This is a critical factor that should be taken into account when designing a resource provisioning algorithm.

B. Transitions

Every node addition to or removal from a *NoSQL*-database does not happen instantly. The time it takes for a new node to become operational in a cluster or an operating node to cease operation may range from a few milliseconds to several minutes or hours. A newly instantiated node might need to deploy software artifacts, edit property files and/or start groups of services. Also, in *NoSQL*-databases, a node addition means that data will typically be shipped and replicated over the network. Apart from any requisite data transfer, the cluster may need to update its own internal data structures and indices to reflect the new state. The above requisite operations consume resources from both new and old nodes and may entail major overheads in terms of CPU-cycles, memory, disk and occasionally, network bandwidth. If these operations are not carefully considered, they could easily push the cluster into an unstable state.

C. Cluster Heterogeneity

Cloud infrastructure typically exhibits significant heterogeneity in terms of CPU, memory, disk(s) and NICs of cloud infrastructure nodes [2], [10]. This is due to *private CSPs* incrementally upgrading their internal machinery as well as *public CSPs* competing against each other and frequently changing their rental offerings to better match client requests [11]. An adaptive cloud-based application that aims to exploit the best out of the available resources should leverage the heterogeneity of cloud machines accordingly. In our work, we handle this problem by profiling *NoSQL*-databases such as the ELASTICSEARCH [6] under different cluster configurations. We use *linear regression* and *support vector regression* to predict performance metrics of future deployment outcomes such as estimated throughput and expected percentage of operations with latencies that violate the *SLA* of the application.

III. Building an Application Performance Model

To effectively decide which nodes will be part of a cluster, we want to successfully estimate the behavior of the purported configuration once provisioning takes place. We accomplish this by creating a performance model for the *NoSQL*-database under deployment, so we use this model to estimate the cost of a newly introduced configuration as *SLA* violations can be traded off with leasing costs from *public CSPs*. Predicting the performance of the *NoSQL*-databases with reasonable accuracy is key to our provisioning method. As queueing analytic based models cannot deliver viable solutions [12], [13], we resort to an empirical modeling approach. Our approach initially carries out selective stress tests on different cluster configurations for the *NoSQL*-database at hand [14]. As this process is carried out offline, no penalties are imposed during the normal execution of the *NoSQL*-database. It then creates a forecasting model to offer configuration suggestions based on data collected. We use linear regression and support vector regression to predict the performance of potential cluster configurations to determine whether tossing *NoSQL*-databases out to *public CSPs* is beneficial.

A. Profiling Experiments

We use a modified version of the *Yahoo! Cloud Serving Benchmark (YCSB)* [15] to profile ELASTICSEARCH V0.20.6, a popular *NoSQL*-database that uses sharding [8] to distribute horizontal partitions of data to different Virtual Machines (*VMs*). ELASTICSEARCH V0.20.6 tends to distribute its shards equally to all of nodes that participate in the cluster; to this end, we seek to ascertain how ELASTICSEARCH behaves under variable number of CPU–cores, CPU–frequency, memory, and *VMs*.

In the standard *YCSB* edition, a client either creates or joins an existing cluster of nodes. Hence, it is likely that at least a portion of the requested data may reside in a shard located on the client's *VM*. This is surely an unusual setting for a cloud setup as in cloud environments, the back-end components handling data are often separate from application clients. ELASTICSEARCH features *non-data nodes* that can function as load-balancers. In our modified *YCSB*, a client simply connects to a load-balancer node to access data from all shards dispersed throughout the network. This layout better reflects realistic deployments of *NoSQL*-databases.

We perform a number of *YCSB* runs on ELASTICSEARCH with different targeted throughput in clusters with up to 6 nodes and a single load-balancer node while varying the number of CPU–cores, CPU–frequency, memory, and *VMs* of the cluster. We added 3,000,000 records to the ELASTICSEARCH database and then performed 500,000 *GET* operations following a uniform distribution based on the record *ID*. We measured the following:

- throughput of each cluster configuration,
- percentage of operations per time unit that violates *SLAs*; we term this as *DROP*: *delayed response operations percentage*,
- transition cost and delay for data–node addition/removal.

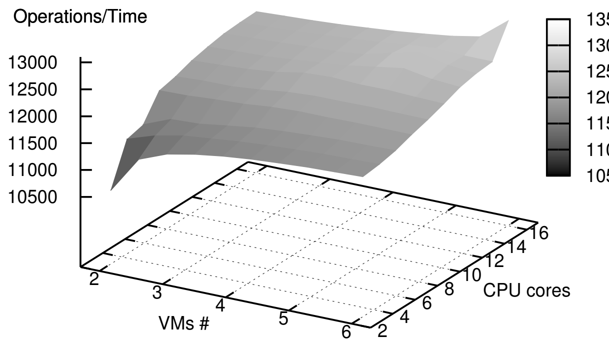
We assume that a request completing in more than *5ms* generates an *SLA* violation. For brevity, we omit showing the profiling experiments for CPU–frequencies. In general, the CPU–frequency profiling results follow similar trends with those of RAM. Below, we outline the key findings from profiling the above *NoSQL*-database in a *private CSP*.

- *Throughput:* Fig. 2a shows that as *VMs* are added, throughput increases almost linearly. The same behavior is observed for CPU–cores as more *GET* operations can be handled. Similar trends are depicted in Fig. 2b, where the size of RAM varies. We find that throughput is affected less by RAM and CPU–frequency as *GET* operations scale out better (i.e., adding more *VMs*) than scale up (i.e., by increasing memory and CPU–frequency).
- *DROP:* Results for requests missing their *SLAs* are not as clear cut as those of throughput. Fig. 3a reveals that the resulting *DROP* maintains high margins between the average value and the maximum and minimum values attained as we increase the number of *VMs*. Similar observations hold for *DROP* rates while varying CPU–cores and RAM in Figs. 3b and 3c; they demonstrate behavior with no clear trends. Thus, the above three profiling viewgraphs cannot lead to any strong conclusions regarding *DROP* prediction. Consequently, we resort to machine learning techniques to more effectively forecast *DROP* values.
- *Transition Cost and Delay:* We have performed experiments where we add or remove data–nodes and monitor how the throughput of the cluster is affected. In these profiling experiments, we ascertained that the transition cost (i.e., transporting shards) is almost independent of the configuration of the nodes that participate in the cluster. Although bandwidth linearly affects costs and delays, in an environment where multi-*Gbps* networks connect private and public *CSPs*, this factor becomes an invariant for modeling purposes.

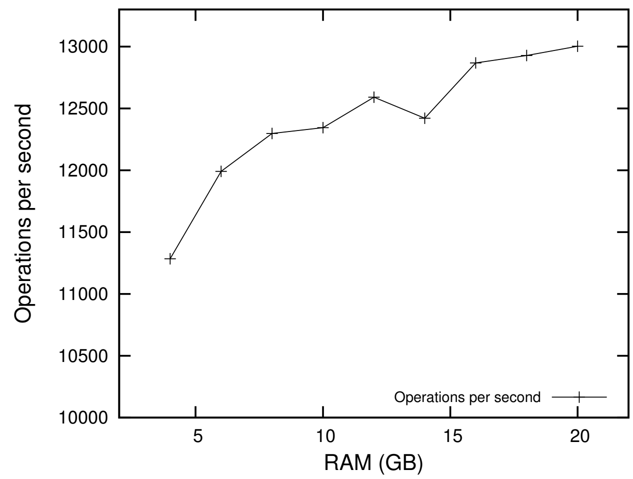
B. Forecasting Models

Our forecasting model takes as *input* a set of *VMs* to be possibly incorporated into the operational cluster along with a number of parameters that include: *i*) *public CSPs* from which to lease the *VMs*, *ii*) CPU–cores, *iii*) CPU–frequency, *iv*) size of RAM, *v*) number of *VM* nodes. The outcome of the forecasting model states how the re-aligned cluster would perform should the additional *VMs* from the *public CSPs* be included as part of the cluster. The *output* of the model consists of the following anticipated rates and/or values: *I)* throughput rate, *II) DROP* rate, as well as *III)* transition cost, duration, and delay. Below, we discuss how we deliver these three rates and costs.

The outcome of our black-box profiling yields selected measurements for specific coordinate values in a multidimensional

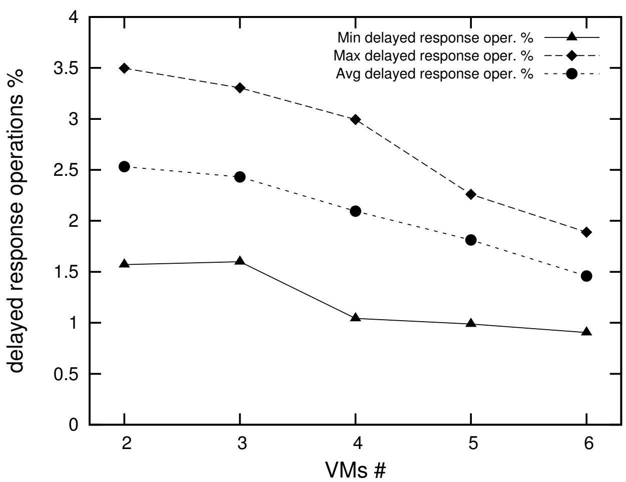


(a) Throughput: Operations per second over VMs # and CPU–cores

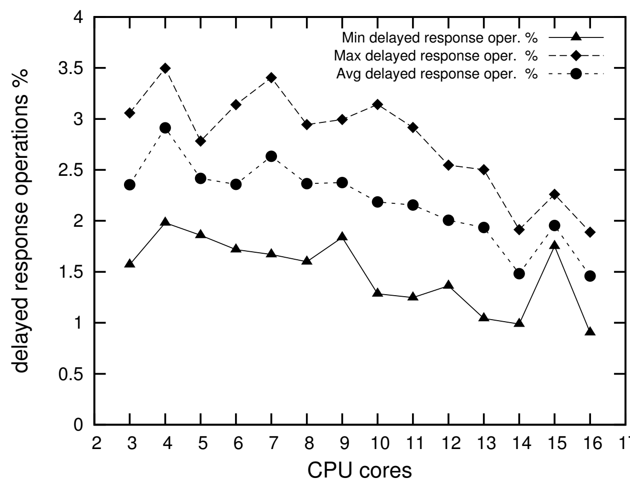


(b) Throughput: Operations per second over RAM

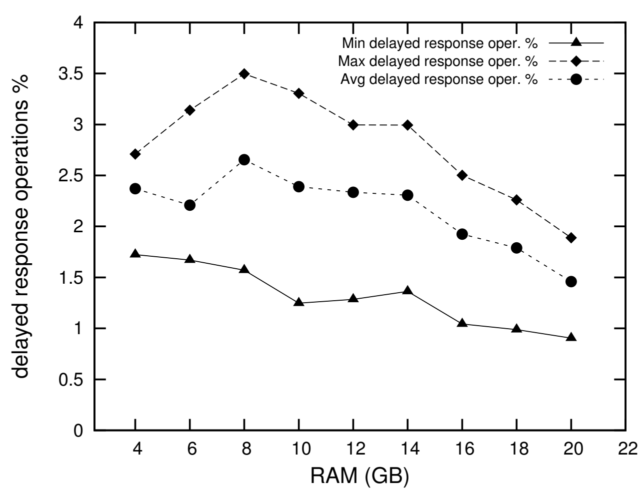
Fig. 2: ELASTICSEARCH throughput



(a) *DROP* over VMs #



(b) *DROP* over CPU–cores



(c) *DROP* over RAM

Fig. 3: Percentage of operations missing their *SLA* (*DROP*) in ELASTICSEARCH

space. If we knew every possible value in this space, we would be able to derive the best solution for a given provisioning. However, this is infeasible, so we use approximate estimation methods to produce the output rates/values of the model. In particular, we use predictive techniques [16] to estimate expected rates for throughput and *DROP*. These techniques need an adequate size of training data to be well calibrated. Moreover, the training set has to consist of a representative sample of cluster configurations to both accurately predict the future and remove outliers. We experimented using the *RapidMiner* [17], a software platform for machine learning, to ascertain pros and cons of various predictive techniques and we have identified the following options (cases *I* and *II* below) to respectively estimate throughput and *DROP* rates:

I) *Linear Regression for Throughput:* Fig. 2a clearly shows that the cluster throughput increases linearly with the number of *VMs* and/or CPU–cores. Consequently, using linear regression to estimate throughput rates for cluster configurations that have not been evaluated in the stress-test profiling phase is the intuitive choice. In contrast, the addition of RAM in the cluster leads to less discernible gains for throughput (Fig. 2b). A similar trend to that of RAM occurs with CPU–frequency as well. While using linear regression for throughput estimation, we place less importance on the RAM and CPU–frequency values than the number of *VMs* and CPU–cores used by using appropriate weights; the latter are computed during the fitting process.

II) *Support Vector Regression (SVR) for DROP Rate:* Fig. 3 collectively reveals that although the average *DROP* rate decreases as the values of input variables increase, the minimum-to-maximum range for resulting *DROP* values remains large. There are undoubtedly complex relationships between the five input variables and the expected *DROP* rate that are impossible to capture using linear estimation techniques. The presence of multidimensional variables along with their complex relationships makes the *SVR* approach suitable for our case as it can more effectively predict the *DROP* rate.
SVR maps data from their own original space into a higher–dimension feature space and then computes an optimal regression function in this new feature space [18]. This data transformation is carried out through the mapping: $v \rightarrow \varphi(v)$, where $v = (v_1, v_2, \ldots, v_n)$ is a vector of independent variables; in our case, v represents the n values of our *input variables*[1] making up a single data point. The mapping is assisted by kernels that essentially bypass the explicit use of $\varphi(.)$ to transform data to the new feature space. Kernels are realized as the dot product of two vectors i and j in the feature space as follows: $k(v_i, v_j) = \varphi(v_i) \cdot \varphi(v_j)$ Among popular non–linear kernels, we use the *Gaussian Radial Basis Function (RBF)* as the *DROP* rate depicts non-linear behavior and *RBF* proves to be the most accurate. The *RBF* kernel is: $k(x_i, x_j) = \varphi(x_i) \cdot \varphi(x_j) = e^{-\gamma \|x_i - x_j\|^2}$, where γ is an adjustable positive variable.

III) *Transition Cost and Delay:* Using additional *VM*(s) from possibly different *public CSPs* involves a delay that is required to ship a shard to the designated *VM*(s). This transition can be expressed as a function over time as follows:

$$transition(t) = \begin{cases} 0 & t \in [0, delay] \\ tr\_overhead & t \in (delay, T] \end{cases}$$

where *delay* = $D_{startup|shutdown}$,
T = *delay* + *tr_duration*,
tr_duration = *duration_per_shard* * *moved_shards*,
tr_overhead = *overhead_per_shard* * *moved_shards*
and *moved_shards* = max(
*added_nodes * (total_shards / new_cc_nodes),*
*removed_nodes * (total_shards / cc_nodes)).*

Here, $D_{startup|shutdown}$ represents the fixed time that a *VM* takes to either start up or shut down, *moved_shards* is the number of shards to be moved when the cluster configuration changes, *added_nodes* and *removed_nodes* are the number of the nodes added to or removed from the cluster configuration respectively, *new_cc_nodes* and *cc_nodes* are the number of the nodes in the new and current cluster configurations respectively, *total_shards* is the number of shards involved in the *NoSQL*-database, *duration_per_shard* is the overhead, in seconds, that each moved shard adds and *overhead_per_shard* is the overhead in operations per second that each moved shard generates. Table I shows observed average values of representative factors involved in the estimation of *Transition Cost and Delay*. Multiple experiments yield invariable values indicating constant overhead behavior.

TABLE I: Transition cost values

Variable	**Value**
$D_{startup}$	3 secs
$D_{shutdown}$	2 secs
duration_per_shard	4 secs
overhead_per_shard	1000 oper/sec
total_shards	10

IV. Look-Ahead Optimization for *CSPs*

Our main objective is to identify the least expensive combination of nodes that collectively satisfies the constraints imposed by the cloud applications(s). These constraints can be either strong (i.e., calling for *SLA* penalty minimization) or weak (i.e., seeking to lower the *CSP* expenses). Either way, the selection of *VMs* and the identification of a "cluster" to be used highly depend on the current configuration on which the application runs as well as its anticipated workload characteristics. [10] showed that service provisioning is *NP*-hard and suggested heuristics to prune the solution space by

[1] In particular, five values corresponding to (i) *public CSPs* used, (ii) CPU-cores, (iii) CPU-frequency, (iv) size of RAM and (v) number of *VMs*.

limiting either the depth of the ensued search tree or the time period within which a viable solution is sought.

We employ *Look-Ahead Optimization (LAO)* to identify a (sub)optimal selection of a new cluster configuration by examining all possible paths that are feasible at a specific point in time. Our approach uses the current state of affairs within the cluster and seeks to optimize future states. As in [5], we assume a relatively accurate predictor for workload characterization to predict the outcome of a future cluster configuration.

A. Receding Horizon Control (RHC)

is a *LAO*–method that iteratively solves an optimization problem for a fixed time interval while taking into account current and future constraints; it has been successfully used for resource provisioning [4]. *RHC* functions in a recurrent fashion as follows:

- *S1)* At time k, find an optimal solution for the specific and fixed–period $[k, k+T]$ while considering current allocations and forthcoming constraints.
- *S2)* Apply only the first element of the above optimal sequence.
- *S3)* Shift time t to $k+1$ and repeat the process for the interval $[k+1, \ldots, k+T+1]$.

Should there be no (other) external factors that affect the cost computation of the solution sought in step *S1* above, the *RHC* finds the optimal solution for the given time-window T. We assume the following:

- *A1)* J represents the sum of the current[2] operational/leasing cost of the *VM* resources placed in a cluster from both *private* and *public CSPs*, the costs of incurred *SLA* violations and *public CSP* pay-backs, and the imposed transition cost for a unit of time,
- *A2)* x_t represents the state of the cluster in terms of the set of allotted resources at time t,
- *A3)* u_t entails all feasible transitions to reach a new cluster configuration at time t; this set of transitions involves additions or removals of *VMs*,
- *A4)* $\{x_t\}$ is the sequence of all states generated in the period $k \ldots t$,
- *A5)* $\{u_t\}$ is the sequence of all transitions that have taken place within period $k \ldots t$,
- *A6)* $x_{i+1} = f(x_i, u_i)$ for $i = k, \ldots, k+T$, where f is the function that maps a state x_t to the next x_{t+1} according to u_t input choices available at time t,
- *A7)* $cost(\{x_i\}, \{u_i\}) = \sum_{i=k}^{i=k+T} J(x_i, u_i)$ represents the cumulative cost incurred while following the $\{x_i\}$ sequence with the corresponding $\{u_i\}$ sequence and J is the cost function defined above in *A1*.

In step *S1* of the *RHC*, we identify the optimal solution as the one that provides as $cost_{opt} = \min\ cost(\{x_t\}, \{u_t\})$. The solution of the above optimization problem leads to a sequence of suggested cluster configurations $\{x_k, ..., x_{k+T}\}$ and a respective sequence of transitions $\{u_k, ..., u_{k+T}\}$ that eventually take place. The sequence $\{x_k, ..., x_{k+T}\}$ corresponds to a path having the minimum cumulative cost in the time–window elapsed between $k \ldots k+T$.

B. Selecting the Time-Window Period

The time-window is a fundamental *RHC* parameter as it designates the depth in which a solution is to be searched and presents a number of trade-offs. On the one hand, a short window might miss a number of good long-term changes if it cannot capture significant future workload changes. On the other hand, a long time-window affects the execution time of the algorithm as it may introduce exponential complexity. A viable choice for time-window length should be able to capture at least a few complete transitions in the make up of a cluster as well as pertinent overheads. Any benefits in the operation of a re-aligned cluster will be reaped after the transition eventuates. Hence, it is also imperative that the time-window be a function of the average duration of the transitions.

[2]based on time t.

C. Resource Provisioning Algorithm

Algorithm 1 recursively determines the cost as well as the entire sequence of cluster configurations generated within the time-window [*start_time*, *end_time*] that imposes minimum cost for the *private CSP* (*best_configs*). Starting from the initial cluster configuration (*cc*), the algorithm examines all possible configurations that can be reached while trying to identify the next configuration possibly involving *VMs* from *public CSPs* as well. The invocation of POSSIBLE_CLUSTER_CONFIGS() produces feasible configurations by taking into account the replication factor of the *NoSQL*-database. The replication factor designates the number of redundant copies of shards, and so, it limits the number of *VMs* that can be removed from a cluster during a single transition.

Algorithm 1 Provisioning Best-Plan

```
procedure BEST_PLAN(cc, start_time, end_time, best_cost, best_config)
    for all cl in POSSIBLE_CLUSTER_CONFIGS(cc) do
        tr_delay, tr_duration, tr_overhead = TRANSITION(cc, cl)
        time = start_time
        if tr_delay + tr_duration + time > end_time then
            cost = 0
            tr_delay = 0
            tr_duration = end_time - start_time
        end if
        cost = PARTIAL_COST(
                        cc, cl, tr_duration, tr_delay,
                        tr_overhead, start_time)
        time += tr_delay + tr_duration
        configs = [ ]
        if time < end_time then
            p_cost, configs = BEST_PLAN(
                        cl, time, end_time, best_cost, best_configs)
            cost += p_cost
        end if
        if cost < best_cost then
            best_cost = cost
            best_configs = cl + configs
        end if
    end for

    return (best_cost, best_configs)
end procedure
```

A possible change in cluster configuration implies transition costs for resource re-alignment that may require non-negligible operations and takes a *duration* interval to unfold. Moreover, the transition may have a latency, termed *delay*, before it actually completes. TRANSITION() estimates for transition delay, duration and overhead based on the suggested performance model of Section III. These three values, along with current and a feasible new cluster configuration, are furnished to Algorithm 2 (PARTIAL_COST) to assess the cost of a proposed transition; the latter is essentially the factor J defined in $A1$ above. Subsequently, Algorithm 1 shifts the *start_time* of the time-window by as much as the time required to complete the suggested transition. The algorithm then moves to compute the rest of the optimal cluster configuration sequence in a recursive manner always using the first element of the remaining sequence as the pivot for its exploration. In this regard, the recursive calls along with the loop over the set produced by POSSIBLE_CLUSTER_CONFIGS(), build a tree with all feasible configuration sequences within the sought time-window. While this tree is traversed, the loop keeps the sequence(s) with the minimum partial cost, which effectively results in the optimal cluster configuration sequence for the time-window.

Algorithm 2 realizes the operation of PARTIAL_COST() and computes the entire cost including transitioning, violation of *SLA*, pay-backs from *public CSPs*, and operational overheads, for a suggested new configuration. PARTIAL_COST() takes as input the current configuration (*old_cl_config*), the proposed new configuration (*cl_config*), the estimated transition duration (*tr_duration*), delay (*tr_delay*) and overhead (*tr_overhead*) as well as the start time (*start_time*) and returns the total cost of the transition period. The additional work that a *private CSP* has to undertake to bring the cluster to its new suggested state is designated by the *tr_delay* interval. The latter corresponds to the latency of the transition and through this period, the cluster appears as operating its prior configuration (*old_cl_config*). When *VMs* are moved in and out of a configuration, they remain idle during this process –no service is provided– and *tr_delay* accounts for the effort required to accomplish this re-alignment of resources. As soon as *tr_delay* is accounted for, the transition is in progress. In this transition phase, the operating *VMs* of the cluster involve elements from both old and new configurations as: *1*) newly introduced *VMs* become fully functional after the completion of the transition, and *2*) *VMs* to be removed are released immediately after *tr_delay*.

Algorithm 2 Partial Cost

```
procedure PARTIAL_COST(old_cl_config, cl_config, tr_duration, tr_delay,
tr_overhead, start_time)
    op_cl_config = UNION(cl_config, old_cl_config)
    // the total nodes allocated during tr_delay

    tr_cl_config = INTERSECT(cl_config, old_cl_config)
    // the fully functional cluster during the transition

    cost = 0
    time = start_time
    tr_end_time = start_time + tr_delay + tr_duration
    while time < tr_end_time do
        wl = workload[time]
        // workload is the array of predicted future workload
        // (operations per time unit)

        if time - start_time < transition_delay then
            p_cost = CLUSTER_CONFIG_COST(
                        op_cl_config, old_cl_config, wl, 0)
        else
            p_cost = CLUSTER_CONFIG_COST(
                        cl_config, tr_cl_config, wl, tr_overhead)
        end if
        cost += p_cost
    end while

    return cost
end procedure
```

For a specific point in time, CLUSTER_CONFIG_COST() computes the operational and penalty costs incurred by possible *SLA* violations. Algorithm 3 takes as input the *VMs* currently allotted (*op_cl_config*), the cluster configuration (*cl_config*), the expected *workload* at this time instance (expressed in number of operations per time unit) and the transition overhead (*tr_overhead*); CLUSTER_CONFIG_COST() returns the operational cost of the cluster configuration during the time unit in question. To compute potential *SLA* violations, we use *linear* and *support vector regression* to gauge the maximum throughput of a given cluster configuration and the *DROP* rate (Section III). The above is accomplished by respectively invoking PREDICT_THROUGHPUT() and PREDICT_DROP(). The fraction of *SLA* violations accorded to *VMs* coming off *public CSPs* yields pay-backs to the *private CSP*. OPER_CL_COST() determines the sum of the current rental/operational cost of each node within *op_cl_config* depending on whether the *VMs* in question belong to either a *public* or the *private CSP*.

TABLE II: *VM* specifications

CSP	CPU cores	CPU freq (GHz)	RAM (GB)	Penalty per *SLA* violation (in monetary units)	Cost (per sec)
prv	4	3.2	8	–	35
prv	2	2.4	6	–	40
pub1	4	2.4	3	0.3	55
pub1	4	2.4	4	0.15	60
pub2	4	3.2	8	0.25	65
pub2	4	3.4	8	0.2	75

Algorithm 3 Cluster Configuration Cost

```
procedure CLUSTER_CONFIG_COST(op_cl_config, cl_config, workload,
tr_overhead)
    total_workload = tr_overhead + workload
    cluster_throughput = PREDICT_THROUGHPUT(cl_config)
    handled_workload = min(cluster_throughput, total_workload)
    drop = PREDICT_DROP(cluster_config)
    violations = max(total_workload - handled_workload, 0)
    // violations due to throughput

    violations += handled_workload * drop
    // violations due to DROP

    violations_per_node = violations / cl_config.nodes_no
    payback = 0
    for node in cl_config do
        if node.belongs_to_public_csp then:
            payback += node.sla.penalty * violations_per_node
        end if
    end for
    total_penalty = app_sla_penalty * violations - payback
    // app_sla_penalty is the penalty for each SLA violation
    // in the application

    return OPER_CL_COST(op_cl_config) + total_penalty
end procedure
```

V. Evaluation

A. Our Cost Model vs. SLA-Cost Minimization

We present key evaluation results derived with a prototype that implements our suggested provisioning approach. Our system is written in *Python v.2.7.5* and uses the *scikit-learn* library [19] for *SVR* computing. Table II depicts the key

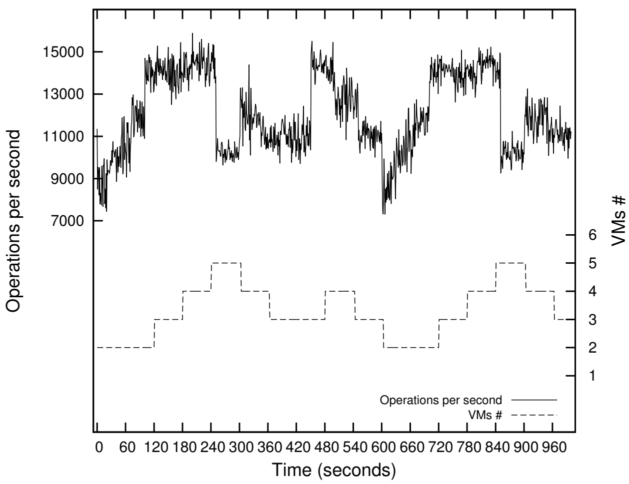


Fig. 4: *RHC* with *SLA*-Cost Minimization

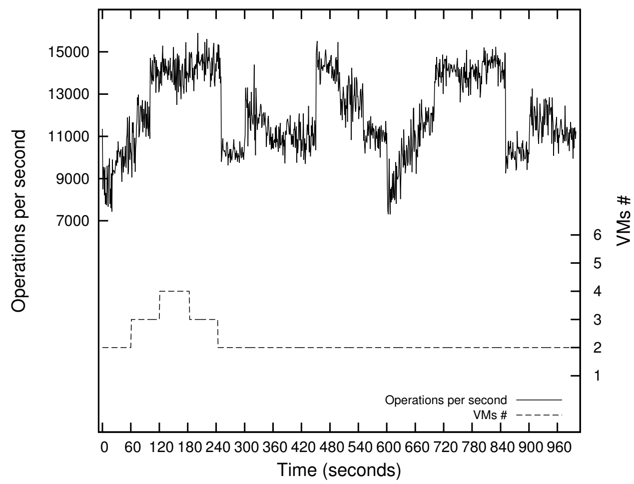


Fig. 5: *RHC* with our Cost Model

features of *VMs* used in experiments along with respective costs and *SLA* violation penalties as advertised by *public CSPs*.

We set the penalty for each *SLA* violation of the application running to 0.3 monetary units and the time-window size to 60 *secs*. In the beginning of every experiment, a cluster consists of 2 *VMs* from the *private CSP*. For simplicity, we add/remove 1 *VM* during each transition every 60 *secs*. We investigate the following:

- how our cost model (*A1*) fares with the conventional *SLA*-cost minimization approach,
- the effect that the transition cost has on provisioning and
- how our approach reacts in short/long workload spikes.

The workload of the experiment was created using the *YCSB* and we employed epochs demonstrating periodic behavior. Every such epoch has length of 600 *secs* (i.e., top curves in Figs. 4, 5, and 6). Within every epoch, the workload is gradually increased and remains high for about 250 *secs*. Then, it is decreased abruptly until a short spike is met on the $300th$ *sec*. After the spike the workload's trend remains unchanged until another spike is met on the $480th$ *sec*. Then workload gradually decreases until the end of the epoch. The random generators used to produce the workload follow uniform distributions. Although, we run numerous and lengthy experiments, we only report representative results from a specific range of $1{,}000$ *secs* for readability purposes.

We use *RHC* as the main framework for provisioning and we compare our cost model with that of the widely-used *SLA*-cost minimization approach [3], [16]. Both techniques are deployed in a *private/public CSP* infrastructure and we track the number of allocated *VMs* over time for the execution of a synthetic workload, which consists of a diverse number of *GET* operations per *sec*. We also monitor the following accrued costs as reported by the (*YCSB*) client: *1*) the penalty cost of the *SLA* violations, *2*) the operational cost of the *private CSP* *3*) the lease cost of *VMs* rented from a *public CSP* *4*) the penalty payback, and *5*) the transition cost. The *SLA*-cost minimization approach involves only the penalty cost due to *SLA* violations and it does not include cluster operational costs, pay-backs from *public CSPs* as well as transition costs (i.e., *tr_overhead* is 0).

Figs. 4 and 5 depict the number of *VMs* used by the *SLA*-cost minimization approach and our provisioning approach respectively. Fig. 4 shows that the *SLA*-cost minimization approach tends to allocate more *VMs* to handle the workload and to maximize *QoS*. The conventional *SLA*-cost minimization approach does not take into account the operational cost of the *VMs* in the cluster and thus, often chooses configurations with the highest performance capacity. This approach appears to "encourage" changes in cluster configurations, as there is no consideration for transitional costs.

In contrast, Fig. 5 shows that our approach requires fewer *VMs* for most of the time and releases them as soon as they are not needed to reduce operational cost. The transition cost makes our approach more conservative to changes. In our approach, there are only 4 encountered configuration changes compared to 13 in the *SLA*-cost minimization method. By considering operational/transition costs as well as pay-backs, our approach tries to balance performance capacity on the one hand, and the investment in new cluster configurations with more/fewer resources on the other. This is why our approach uses only 2 *VMs* to handle the workload in time interval $240{-}1{,}000$ while the conventional *SLA*-cost minimization method exploits most of available *VMs* in the experiment. Note that in our approach the last 2 *VMs* are different than the initial. In fact, they both belong to public *CSPs* and the reason the algorithm does not decide to move to another cluster configuration is because the payback from these *VMs* balances the total cost. Also, our approach decides the first transition before the *SLA*-cost minimization approach. This is due to the fact that the node selected by our approach is the first that belongs to a public *CSP* and hence, the payback from this node results in a better solution. In the *SLA*-cost minimization approach this does not happen since the workload can be handled by the initial cluster configuration since it is fairly

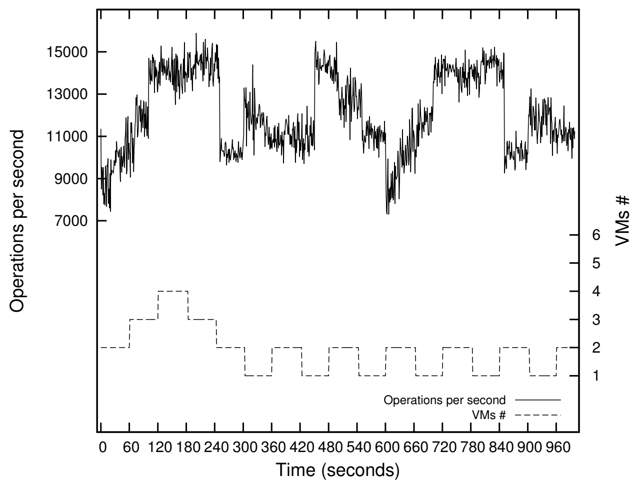


Fig. 6: Our Provisioning Approach with Lower Transition Cost

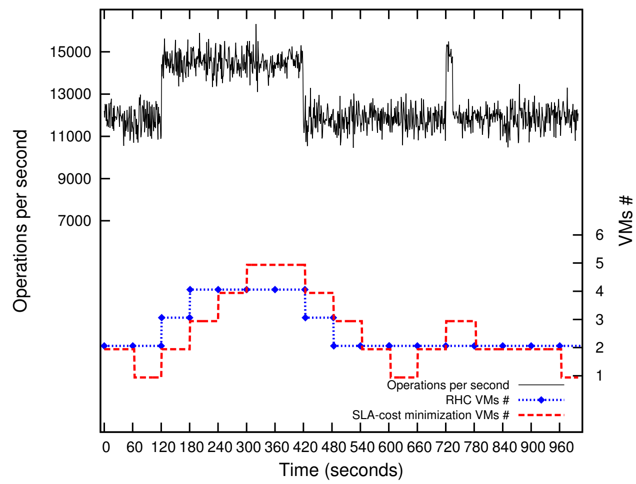


Fig. 7: Long and Short Workload Spikes

low (less than 11,000 operations per *sec*).

When it comes to costs, the *SLA*-cost minimization approach is on average 475% more expensive than our approach just for the limited 1,000 *secs* of observation. Since the *SLA*-cost minimization approach ignores the transition cost, it falls into many situations where the cluster is overloaded, hence the current throughput drops dramatically. The reduction of the throughput in the *SLA*-cost minimization approach results in 41% fewer operations completed in the reported period.

The above results clearly show that the penalty minimization of the *SLA* violations does not lead to the minimization of the total cost. As our approach can better capture the actual costs involved in the execution of workloads, it is of substantial value to *NoSQL*-database owners.

B. The Effect of Transition Cost

We next evaluate how transition cost affects the cluster configuration changes. When a cluster that runs a *NoSQL*–database allocates or deallocates *VMs*, shards need to be transported. The overhead of this process is the transition cost, which is a key factor for provisioning since it indirectly affects the total cost of the *private CSP*. Fig. 6 depicts the results of the same experiment as that of Fig. 5 but with lower transition cost. Here, we set the *tr_overhead* of Table I at 90% less than the corresponding values of the first experiment. We find that the number of transitions increases from 4 (in Fig. 5) to 16 as transition costs decrease. In the original experiment, high-transition configuration changes are not encouraged by our approach, as the potential benefits are less than the incurred cost. More specifically, the provisioner decides to release and acquire a *VM* continuously after 240 *secs* since the transition cost has been reduced and the cluster can handle the workload with only 1 *VM*.

With lower transition costs, our *RHC*–based provisioning becomes more aggressive in tracking even rapidly changing workload trends. For an effective transition to occur, the length of the time-window used must be longer than the respective transition cost. *NoSQL*-databases occasionally present varying transition costs. When these transition costs are also high, these systems are less less effective at handling rapidly changing workloads. Hence, the transition cost is a key factor when using a *NoSQL*-database as it is equally critical to throughput and *DROP* attained when the workload displays abrupt variations.

C. Long vs. Short Workload Spikes

In this experiment, we investigate how our *RHC*-based approach compares with *SLA*-cost minimization when there are spikes in the workload. Spikes are often met whenever the user requests are increased for some reason (i.e., flash crowds).

Fig. 7 shows a workload featuring a long and a short spike at time intervals $120-420$ and $720-735$, respectively. The figure also depicts how our *RHC*-based provisioning and the *SLA*-cost minimization approaches behave in both instances. Our approach handles the long spike by adding *VMs* while it essentially ignores the short spike. During the short spike, the cluster does not move to another configuration to handle this short-lived demand as the total cost for a possible transition is greater than the cost of inaction. At the end of the long spike, the *SLA*-cost minimization method ends up having 5 out of 6 of the available *VMs*, which leads to a long deallocation period as deallocations are not instant. Hence, unnecessary *VMs* continue to be allocated for some time after the spike ceases which results in higher operational cost. During the short spike, the conventional *SLA*-cost minimization method attempts to allocate additional resources being oblivious of what lies ahead. In this specific instance (i.e., time interval $720-735$), the transition costs involved are of similar length to the spike in question. Thus, additional *VMs* become functional beyond the time at which the spike ends yielding a resource thrashing situation. Our *RHC*-based provisioning avoids such thrashing because it continually evaluates the total cost of every feasible sequence of cluster configurations in a time-window and picks the best. As for the cost, the *SLA*-cost minimization approach costs 92% more than our *RHC*-based provisioning approach for the observed period.

VI. Related work

Resource provisioning for cloud-based systems has recently attracted considerable attention. Efforts in [12], [13] attempt to address the problem through the use of queueing theory and respective model building. As cloud systems are inherently complex, involve parallel and concurrent aspects and are built on heterogeneous environments, such queueing theory models are difficult to extend and quickly become intractable. The extensive use of caching and locking policies further exacerbates matters [20]. Sharma et al. [5] present a system that statically searches for best allocation scenarios and then picks one that minimizes migration costs. The work also advocates for the adoption of performance model building through profiling. Roy et al. [4] presented an *RHC*-based approach that minimizes the operational cost of a host–cloud while satisfying all *SLAs*. However, price variation for resources as well as penalty pay-backs from public *CSPs* are not taken into account in the used price model. Goudarzi et al. [12] outline a heuristic approach to minimize the total energy cost of a cloud computing system while keeping the *SLA*-incurred costs low. Although this work appears to incorporate multiple costs into the minimization problem, the use of queueing theory models entails issues similar to those mentioned above. Barker et al. [3] presented a migration approach for multi-tenant databases that utilize a throttling controller; the latter aims to dynamically vary the migration speed to avoid *SLA* violations due to the transition cost imposed by a migration. To the best of our knowledge there is no work that combines penalty pay-back from *public CSPs*, a critical aspect from the *private CSP*'s point of view, and only a few [3]–[5] take into account the transition cost. Our work also takes a holistic approach and addresses resource provisioning through the occasional leasing of *public* resources in a way that minimizes *total cost* for the *private CSP*.

VII. Conclusions & Future Work

In this paper, we investigate how *NoSQL*-databases running on *private* Cloud-Service Providers (*CSPs*) could be partially "tossed out" to opportunistically exploit resources available from *public CSP* counterparts. Such collaborative auto-scaling helps both minimize total cost for the *private CSP*–hosted application and more flexibly address *QoS*-requirements. We presented a resource provisioning approach based on *look-ahead optimization* that leads to lower *CSP* costs for a limited time-window while considering how to best transform the utilized virtual infrastructure over time. We identify key factors that contribute to the *CSP* aggregate cost and propose a cost model that accounts for both direct and indirect penalties to avoid *SLA* violations for the hosted-application(s). Our evaluation demonstrates the benefits of our cost model over the conventional approach of simply minimizing *SLA* cost with reported gains of up to 475% for the conducted experiments. Moreover, we show that the use of a look-ahead optimization technique helps avoid resource allocation thrashing when the workload changes rapidly. We plan to investigate the relaxation of the accuracy of the used predictor, examine the respective ramifications and ascertain the role introduced errors may have in workload estimation.

Acknowledgment: This work has been partially supported by *iMarine* and *Sucre EU-FP7* projects, *ERC Starting Grant* #279237 and a *THALES* grant co-financed by EU-ESF and the Greek NSFR "Education and Lifelong Learning" Program.

References

[1] K. Tsakalozos, M. Roussopoulos, V. Floros, and A. Delis, "Nefeli: Hint-based Execution of Workloads in Clouds ," in *Proc. of the 30th IEEE ICDCS Conf.*, Genoa, Italy, June 2010.

[2] C. Stewart, T. Kelly, A. Zhang, and K. Shen, "A Dollar from 15 Cents: Cross-platform Management for Internet Services," in *USENIX 2008 Annual Tech. Conf. (ATC'08)*, Boston, MA, June 2008, pp. 199–212.

[3] S. Barker, Y. Chi, H. J. Moon, H. Hacigümüş, and P. Shenoy, ""Cut me Some Slack": Latency-aware Live Migration for Databases," in *Proc. of the 15th Int. Conf. on EDBT*, Berlin, Germany, March 2012.

[4] N. Roy, A. Dubey, and A. Gokhale, "Efficient Autoscaling in the Cloud Using Predictive Models for Workload Forecasting," in *Proc. of the 4th IEEE CLOUD Conf.*, Washington, DC, July 2011.

[5] U. Sharma, P. Shenoy, S. Sahu, and A. Shaikh, "A Cost-Aware Elasticity Provisioning System for the Cloud," in *Proc. of the 31st IEEE ICDCS Conf.*, Minneapolis, MN, June 2011.

[6] "Elasticsearch," http://www.elasticsearch.org.

[7] "MongoDB," http://www.mongodb.org/.

[8] R. Cattell, "Scalable SQL and NoSQL Data Stores," *ACM SIGMOD Record*, vol. 39, no. 4, pp. 12–27, May 2011.

[9] H. N. Van, F. D. Tran, and J.-M. Menaud, "SLA-Aware Virtual Resource Management for Cloud Infrastructures," in *Proc. of the 9th IEEE Int. Conf. on Computer and Information Technology (CIT'09)-vol. 2*, Xiamen, China, October 2009, pp. 357–362.

[10] S. Stein, N. R. Jennings, and T. R. Payne, "Provisioning Heterogeneous and Unreliable Providers for Service Workflows," in *Proc. of the 6th ACM Int. Joint Conf. on AAMAS*, Honolulu, HI, May 2007.

[11] M. Wachs, L. Xu, A. Kanevsky, and G. R. Ganger, "Exertion-based Billing for Cloud Storage Access," in *Proc. of 3rd USENIX Conf. on Hot topics in Cloud Computing (HotCloud'11)*, Portland, OR, June 2011.

[12] H. Goudarzi, M. Ghasemazar, and M. Pedram, "SLA-based Optimization of Power and Migration Cost in Cloud Computing," in *Proc. of 12th IEEE/ACM Int. Symp. on CCGrid*, Ottawa, Canada, May 2012.

[13] R. P. Doyle, J. S. Chase, O. M. Asad, W. Jin, and A. M. Vahdat, "Model-based Resource Provisioning in a Web Service Utility," in *Proc. of the 4th USENIX Symp. on Internet Technologies and Systems (USITS'03)*, Seattle, WA, March 2003.

[14] J. Rogers, O. Papaemmanouil, and U. Çetintemel, "A Generic Auto-provisioning Framework for Cloud Databases," in *Workshops Proc. of the 26th IEEE ICDE*. Long Beach, CA: IEEE, March 2010, pp. 63–68.

[15] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan, and R. Sears, "Benchmarking Cloud Serving Systems with YCSB," in *Proc. of the 1st ACM Symp on Cloud Comp. (SoCC'10)*, Indianapolis, IN, June 2010.

[16] S. K. Garg, S. K. Gopalaiyengar, and R. Buyya, "SLA-based Resource Provisioning for Heterogeneous Workloads in a Virtualized Cloud Datacenter," in *Proc. of 11th Int. Conf. on A3PP-Vol. Part I*. Melbourne, Australia: Springer-Verlag, October 2011.

[17] "RapidMiner," http://rapidminer.com/.

[18] V. Vapnik, *The Nature of Statistical Learning Theory*. Berlin, Germany: Springer-Verlag, 1995.

[19] "scikit-learn," http://scikit-learn.org/.

[20] "Couchbase Server Under the Hood: An Architectural Overview," White Paper, couchbase.com, 2013.