Towards Combining Reactive and Proactive Cloud Elasticity on Running HPC Applications

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Keywords: Cloud Utility, High-performance Computing, Live Thresholding, Resource Management, Self-organizing.

Abstract: The elasticity feature of cloud computing has been proved as pertinent for parallel applications, since users do not need to take care about the best choice for the number of processes/resources beforehand. To accomplish this, the most common approaches use threshold-based reactive elasticity or time-consuming proactive elasticity. However, both present at least one problem related to: the need of a previous user experience, lack on handling load peaks, completion of parameters or design for a specific infrastructure and workload setting. In this regard, we developed a hybrid elasticity service for parallel applications named SelfElastic. As parameterless model, SelfElastic presents a closed control loop elasticity architecture that adapts at runtime the values of lower and upper thresholds. Besides presenting SelfElastic, our purpose is to provide a comparison with our previous work on reactive elasticity called AutoElastic. The results present the SelfElastic's lightweight feature, besides highlighting its performance competitiveness in terms of application time and cost metrics.

1 INTRODUCTION

Commonly, HPC applications are executed either on clusters or grid architectures. Maintaining these environments in terms of infrastructure, scheduling, and energy consumption may turn it an expensive solution (Niu et al., 2013). In the HPC view point, a shared characteristic of such environments regards the fixed number of resources to run an application. Due this limitation, deciding the right amount of processes to execute an HPC application can be a difficult procedure. Conversely, cloud computing has been gaining attention in this context thanks to its resource reorganization facility named elasticity (Herbst et al., 2015), which The act of deciding the right amount of cloud computing resources for a parallel application is a nontrivial task and may lead to either under-provisioning or over-provisioning (Nikravesh et al., 2015; Dustdar et al., 2015). Today, most of the elasticity control strategies can be classified as either being reactive or proactive (Farokhi et al., 2015; Nikravesh et al., 2015; Moore et al., 2013). For the first case, typically users define an upper bound t_u and a lower bound t_l in an ad-hoc manner on a target performance metric to trigger, respectively, the activation and deactivation of a certain number of resources (Netto et al., 2014). On the other hand, a proactive approach employs prediction techniques to anticipate the behavior of the system (its load) and thereby decide the reconfiguration actions. The aforementioned requirements are not trivial and sometimes is needed a deep knowledge about the behavior of the system over time (Dustdar et al., 2015; Jamshidi et al., 2014). In this context, we have proposed in previous work a model named AutoElastic (Righi et al., 2015a; Righi et al., 2015b; Righi et al., 2016) which addresses reactive elasticity to reorganize resources for loop-based synchronous parallel applications. Although achieving remarkable performance gains, AutoElastic remains suffering the main problems of reactive elasticity approaches: definition of thresholds and reactivity. In this context, this article presents a new elasticity model called SefElastic, which offers automatic threshold configuration. SelfElastic presents the following contributions to the state-of-the-art when considering the HPC applications and cloud elasticity duet: (i) a modeling of clo-

Facco Rodrigues, V., Righi, R., André da Costa, C., Singh, D., Munoz, V. and Chang, V.
Towards Combining Reactive and Proactive Cloud Elasticity on Running HPC Applications.
DOI: 10.5220/0006761302610268
In *Proceedings of the 3rd International Conference on Internet of Things, Big Data and Security (IoTBDS 2018)*, pages 261-268
ISBN: 978-989-758-296-7

sed control-theoretic (Ghanbari et al., 2011) infrastructure to support the hybrid elasticity behavior on parallel cloud-based applications; and (ii) based on the TCP (Transmission Control Protocol) congestion control, we propose an algorithm named Live Thresholding (LT) to handle application load projection and lower and upper thresholds adaptivity.

2 RELATED WORK

Today, we can cite basically two main types of application workloads that could take profit from elasticity in the cloud (Ghanbari et al., 2011): (i) transactional (Moore et al., 2013; Nikolov et al., 2014); and (ii) batch (*e.g.*, text mining, video transcoding, graphical rendering and parallel applications) (Niu et al., 2013; Righi et al., 2015a). The applications in the first case are built to serve online HTTP clients, being commonly deployed on commercial systems like Amazon AWS, RightScale and Microsoft Azure using reactive elasticity (Nikravesh et al., 2015). Users must complete the rules and the limits of a metric to be monitored as well as the conditions and actions for reconfiguration. Besides graphical and command-line tools, these commercial systems also provide a particular API for resource provisioning and monitoring.

Reactive elasticity is explored in two scenarios: (i) when using the standard technique with static thresholds (Dustdar et al., 2015; Righi et al., 2015a; Righi et al., 2015b; Righi et al., 2016; Galante and Bona, 2015); (ii) when using other techniques to runtime adapt the threshold values (Netto et al., 2014). In both scenarios, there are at least a lower (t_l) and an upper (t_u) threshold that guide horizontal or vertical elasticity. It is unison among the authors that the performance of the threshold-based technique is highly dependent on the selected parameters, even in the second scenario (Farokhi et al., 2015). In addition to performance, energy consumption and cost metrics are also important both at user and cloud administrator perspectives (Righi et al., 2016). Other problems are related to reactiveness to trigger elasticity actions and oscillations on VM allocations.

3 SelfElastic MODEL

We developed SelfElastic with the following design decisions in mind: (i) parameterless, not needing to write elasticity rules, conditions or thresholds at user/programmer perspective; (ii) easy-to-use elasticity service, being provided in a plug-and-play fashion; (iii) without needing any prior information about the application components/phases and without needing previous executions to generate metadata; (iv) lightweight, so not being prohibitive for time-sensitive HPC applications; (v) easy integration with the parallel application, so the processes can be reorganized easily and quickly in the presence of a drop or addition of resources.

3.1 Closed Feedback-Loop Architecture

Aiming at providing a proactive feature, we designed SelfElastic as a closed feedback-loop architecture (Ghanbari et al., 2011), involving two main components: the SelfElastic Manager and the cloud, which is our target system. As illustrated in Figure 1, we have a loop in which the monitoring metrics serve to optimize and predict internal parameters, so triggering or not elasticity actions to support the application historical behavior.

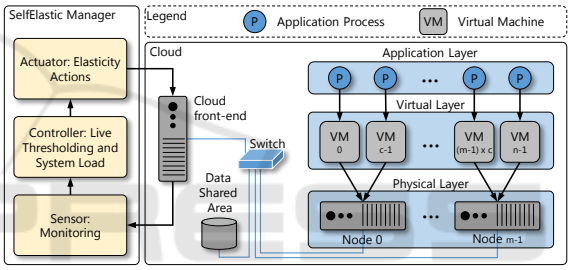


Figure 1: SelfElastic architecture, with two main components: SelfElastic Manager and a cloud-based parallel application (our target system). At the cloud perspective, c denotes the number of cores inside a node, m is the number of nodes and n refers to the number of VMs running application processes, being obtained by $c \times m$.

Our cloud model considers a front-end that acts as a cloud manager to instantiate, deallocate and monitor VMs in the Virtual Layer and a set of homogeneous nodes in the Physical Layer. In addition, the front-end also accounts for answering requests (including the three previous procedures) done with the cloud API by the SelfElastic Manager. Regarding the Application Layer, there is a collection of processes which are instantiated through application-specific VM templates. Each VM is assigned with an template and automatically starts an application process. Depending on the application, different VM templates could start processes with distinct functions.

3.2 Defining the Notion of System Load

The sensor module of SelfElastic Manager monitors CPU load of each VM periodically, passing data to the controller afterward. In turn, the controller apply

algorithms to define load and threshold values. If resource reorganization is necessary, the actuator proceeds elasticity actions using the cloud API. When completing tasks of all modules, the SelfElastic Manager ends a monitoring observation and waits for the next monitoring cycle. One role of the controller is to generate the system load (l) in order to minimize the effect of disturbances or noises on the behavior of the target system. Thus, we are working with time-series and SES (Simple Exponential Smoothing (Herbst et al., 2013)) technique over the CPU load metric of each VM. Equation 1 presents $l(o)$ as the system load at the o^{th} monitoring observation considering n active VMs. This equation is an arithmetic average of the load on each VM, which is computed through $l'(v,o)$. Here, v is a VM index, o is the current monitoring observation and n the number of VMs running application processes (see Equation 2). l' consists in a SES average, where the weight of the current observation o has a stronger influence than $o-1$ in the final calculus (starting from $\frac{1}{2}$, we are using $\frac{1}{4}$, $\frac{1}{8}$ an so on for the weights). The recurrence ends in the $cpu(v,o)$ computation, which returns the CPU load of VM v at observation o.

$$l(o) = \frac{\sum_{v=0}^{n-1} l'(v,o)}{n} \tag{1}$$

$$l'(v,o) = \begin{cases} \frac{cpu(v,o)}{2} & if\ o = 0 \\ \frac{l'(v,o-1)}{2} + \frac{cpu(v,o)}{2} & if\ o \neq 0 \end{cases} \tag{2}$$

3.3 Live Thresholding Technique

The Manager is responsible for retrieving a vector of CPU load from all VMs running slave processes. More precisely, the sensor module of the Manager periodically queries the cloud front-end to capture such data. The mentioned vector is used to compute the system load detailed in Subsection 3.2. Instead of using static thresholds, SelfElastic proposes the dynamic adaption of the lower (t_l) and upper (t_u) thresholds, which are initiated with the values 0 and 100, respectively. We named this novel technique as Live Thresholding (LT), which considers the definition of two procedures: $adapt\_thresholds()$ and $reset\_thresholds()$. The former is computed at each monitoring observation, while the second is called only when an elasticity action takes place.

$adaptThresholds()$ has three parameters: t_l, t_u (both input/output) and $load$ (only input). Firstly, we compute the system load variation considering both current and previous monitoring observations (referred by the indexes o and $o-1$, respectively). This value is assigned to Δl (Equation 3), where function $l()$ was defined earlier in Subsection 3.2. Δl decides which threshold will be updated: (i) if Δl is negative, we are experiencing a decreasing load behavior so t_l is recalculated to handle this situation quickly; (ii) if Δl is positive, the application workload is growing up so t_u is updated to address this situation; (iii) if Δl is equal to 0, threshold adaptations do not occur. Equations 4 and 5 present how new values of thresholds are computed. Contemplating that t_u decreases when updated, it has a lower bound equal to 0. On the other side, an upper bound of 100 is used when computing the new value of t_l.

$$\Delta l = l(o) - l(o-1) \tag{3}$$

$$t_l = Min(t_l + |\Delta l|, 100) \tag{4}$$

$$t_u = Max(t_u - \Delta l, 0) \tag{5}$$

An initial thought to design the $resetThresholds()$ procedure, which has the same set of parameters presented in $adaptThresholds()$, is to reassign these default values at each elasticity action. In our understanding, this threshold resetting strategy may not be the best for elasticity reactivity, since we are putting away all historical data stored in the SelfElastic Manager. Aiming at proposing new forms to reset thresholds, we analyzed the TCP congestion algorithm (Bing et al., 2009). In the TCP protocol, after exceeding a threshold, the window value is incremented linearly by the maximum segment at each burst. So, at each timeout, this threshold is set to half of the current congestion window, and the congestion window is reset to one maximum segment. Thus, we have investigated 6 approaches A_z ($A_z | z \in \{a,b,c,d,e,f\}$) to address threshold adaptivity after an elasticity action:

- When violating t_l we can apply A_a, A_b or A_c in accordance with Equation 6 to compute the new value for t_l, while t_u is redefined to 100;
- When violating t_u we can apply A_d, A_e or A_f in accordance with Equation 7 to compute the new value of t_u, while t_l is restarted as 0.

$$t_l = \begin{cases} 0 & for\ A_a \\ \frac{l(o)}{2} & for\ A_b \\ l(o-1) - \left|\frac{l(o-1)-l(o)}{2}\right| & for\ A_c \end{cases} \tag{6}$$

$$t_u = \begin{cases} 100 & for\ A_d \\ l(o) + \frac{100-l(o)}{2} & for\ A_e \\ l(o-1) + \left|\frac{l(o-1)-l(o)}{2}\right| & for\ A_f \end{cases} \tag{7}$$

SelfElastic always uses a fixed combination of one approach when violating t_l and another for t_u. This results in a notation named LT_{xy}, where x (x is A_a, A_b or

A_c) and y (y is A_d, A_e or A_f) refer to a particular possibility for the lower and upper thresholds, respectively. A_a and A_d simply reset the thresholds to the same values that they were initialized when starting the monitoring. A_b and A_e use the system load after an elasticity action to redesign the thresholds, while A_c and A_f achieve them considering the system load before and after delivering/consolidating resources. SelfElastic is a parameterless model, so the possibility to choose elasticity approaches does not fit our previous design decision. In this way, we conducted experiments with all possibilities of LT_{xy} over eight load patterns considered in the evaluation methodology.

4 EVALUATION METHODOLOGY

We developed a master-slave HPC iterative application that computes the numerical integration of a function $f(x)$ in a closed interval $[a,b]$. The application presents a master process that works in an external loop, where it reads a line from a file that defines the current workload for such an iteration and the number of them. Figure 2 presents the eight loads patterns. To evaluate all LT strategies we firstly executed all combinations of LT_{xy} with the application running the load patterns Constant, Ascending, Descending and Wave. From this evaluation we analyzed the best choice for LT to be considered in the next experiments. All eight loads were executed in three different scenarios: (s1) without cloud elasticity; (s2) enabling self-organizing elasticity management through the functioning of the LT technique; (s3) traditional elasticity approach using static thresholds. While SelfElastic is employed to accomplish the second scenario, our previous work named AutoElastic (Righi et al., 2015a) is adopted to address the third one. Contrary to AutoElastic, here we are using 4 combinations of thresholds: t_l 30% and 50%; and t_u 70% and 90%. Additionaly, our evaluation analyzes the load patterns and the scenarios against three metrics: *time*, *resource* and *cost*.

5 EVALUATION

In this section, we firstly present in Subsection 5.1 an analysis of the cloud and behavior with elasticity guided by all LT ideas. Then, in Subsection 5.2 we focus on evaluating the best strategy for LT. In Subsection 5.3 we analyze the application performance.

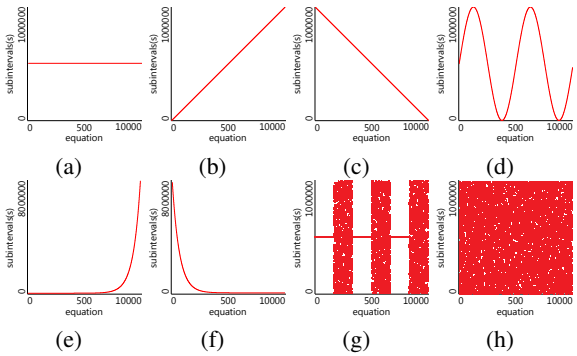


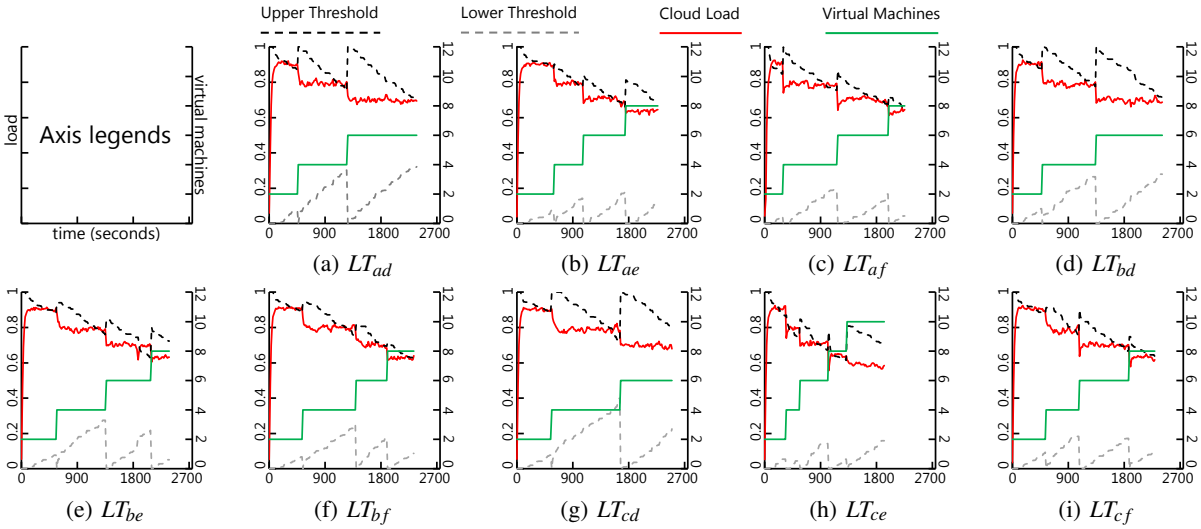
Figure 2: Eight workload patterns considered in the tests: (a) Constant; (b) Ascending; (c) Descending; (d) Wave; (e) Positive Exponential; (f) Negative Exponential; (g) Partial Random; (h)Total Random.

5.1 Analyzing Behavior of the LT Technique

Figure 3 shows all application executions with the Constant load. In this load, violations in the lower threshold (t_l) did not occur. The tiny variations in the load bring similar adaptions in both thresholds. However, t_u is always violated resulting in addition of resources since the load always range the same values and it is nearer the upper threshold (t_u). The figures (b), (e) and (h) present the common use of the A_e approach. In these executions, when an elasticity action was performed, t_u was recalculated to a new value close to the load. It resulted in new violations faster than the other strategies.

The Figure 4 presents LT when executing the Ascending load pattern. As occurred in the Constant load, here the t_l was not violated since the load has a growing trend. In this way, figures (b), (c), (e), (f), (h) and (i) where strategies recalculated the t_u to values near the load, resulted in higher resource consumption and lower execution times. Particularly, executions with the A_f approach achieved up to 12 VMs resulting in faster executions. However, even though in figure (h) the maximum of resources was 10 VMs, this execution achieved the best result considering time. It happened because resources were added faster in the beginning of the execution when comparing with the other approaches. So, with more resources available earlier, the application ended without needing two more extra resources.

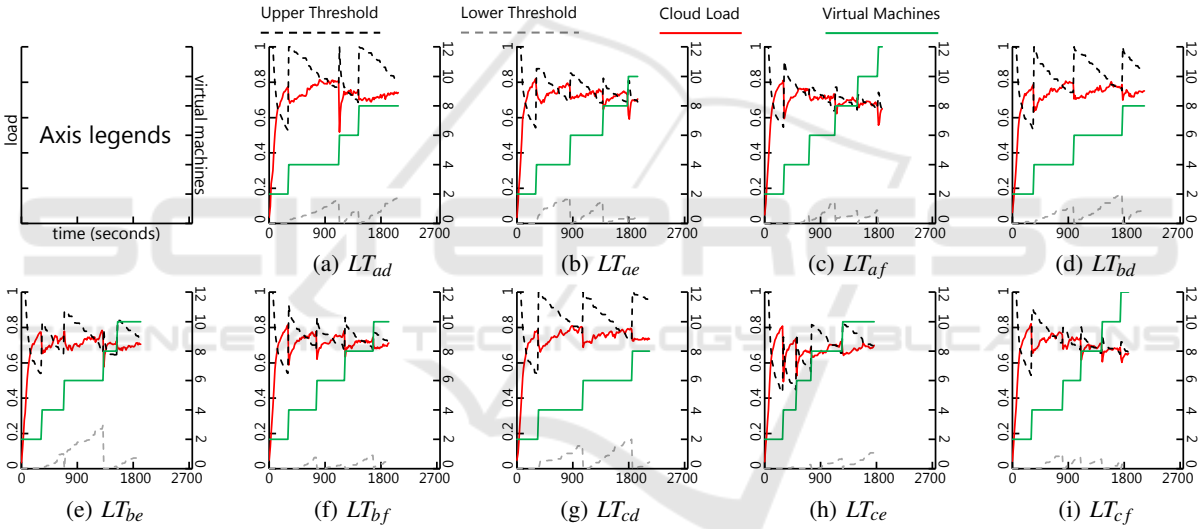
Figure 5 present the behavior of the cloud with the application running with the Descending load pattern. This load has an opposite trend when comparing with the Ascending load. In this way, differently from the loads Constant and Ascending, here t_l has impact in elasticity actions. In addition, as the load started in a high level and decreased slowly, it violated the t_u in all



(a) LT_{ad} (b) LT_{ae} (c) LT_{af} (d) LT_{bd}

(e) LT_{be} (f) LT_{bf} (g) LT_{cd} (h) LT_{ce} (i) LT_{cf}

Figure 3: Historical behavior of cloud parameters and resources when running the application with the Constant load.



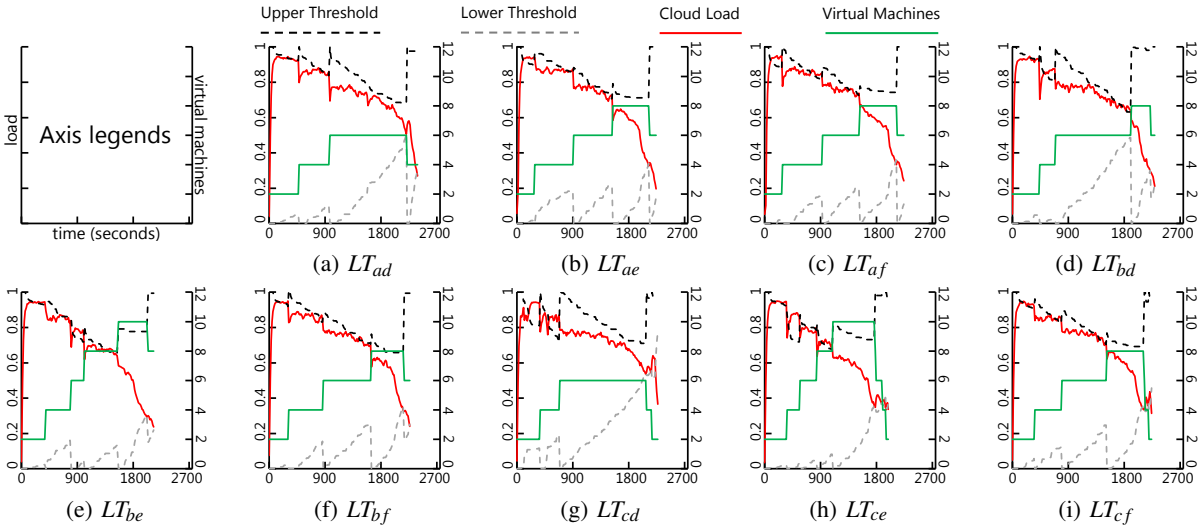
(a) LT_{ad} (b) LT_{ae} (c) LT_{af} (d) LT_{bd}

(e) LT_{be} (f) LT_{bf} (g) LT_{cd} (h) LT_{ce} (i) LT_{cf}

Figure 4: Historical behavior of cloud parameters and resources when running the application with the Ascending load.

executions. The *LT* technique is sensible to small variations in the load, thus t_u decreased hitting the load and it resulted in addition of resources. The first half of execution impacted in performance more than the final part. Resources were added to the cloud in this phase where the load were in high levels. When it started do decrease, in all executions the t_l were violated when the application was near the end. This do not had great impact in performance because the time the application executed with a set new with less resources were to small.

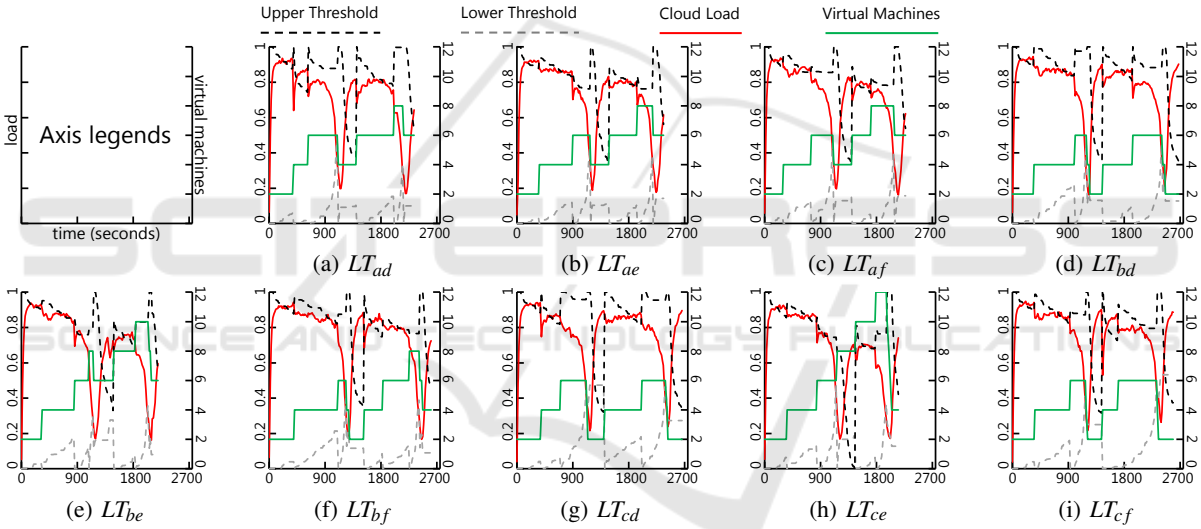
Finally, Figure 6 presents the executions with all *LT* combinations running the Wave load pattern. In this scenario, both t_l and t_u were violated resulting in elasticity actions. Figures (a), (b) and (c) present similar behaviors and the common use of the strategy A_a. The variation of the strategy to recalculate t_u caused variations only in the time when new resources were added. In scenarios presented by figures (d), (e) and (f) the amount of resources available was different in each one. The main difference occurred in (e) since extra resources were added when the load were decreasing near 1000 seconds. It happened because a new elasticity action was already started before and resources were available only at this point. With this extra resources the application execute faster in the last portion of time, resulting in a better performance. Likewise, figures (g), (h) and (i) present *LT* applying A_c and differing the strategy to recalculate t_u. Figure (h) presents a behavior quite different than the



(a) LT_{ad} (b) LT_{ae} (c) LT_{af} (d) LT_{bd}

(e) LT_{be} (f) LT_{bf} (g) LT_{cd} (h) LT_{ce} (i) LT_{cf}

Figure 5: Historical behavior of cloud parameters and resources when running the application with the Descending load.



(a) LT_{ad} (b) LT_{ae} (c) LT_{af} (d) LT_{bd}

(e) LT_{be} (f) LT_{bf} (g) LT_{cd} (h) LT_{ce} (i) LT_{cf}

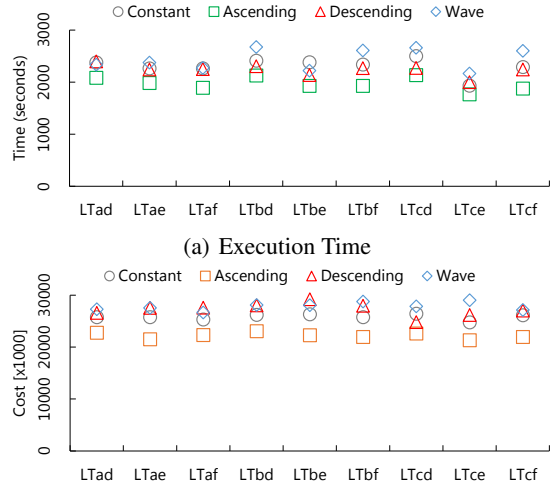
Figure 6: Historical behavior of cloud parameters and resources when running the application with the Wave load.

others two. While in (g) and (i) two elasticity actions were performed to remove resources in the first load drop, in (h) it did no occur. It happened because when the load started to drop by the time 1000 seconds an elasticity action to increase resources was already running. As SelfElastic does not trigger simultaneously elasticity actions, new actions were allowed only when this new resources were available. However, it happened after the load drop and when the application load was already increasing again. As the application keep resources from former actions, the second half of execution was faster in this scenario than all other scenarios.

5.2 Defining Final Approach for LT

Figure 7 presents results of the metrics *time* (a) and *cost* (b) when executing the load patterns Constant, Ascending, Descending and Wave with all possibilities for LT. In the *time* perspective, Figure 7 (a) shows that LT_{ce} achieved better results than the other approaches. This strategy obtained the best mean time (1967 seconds) between all four loads. Although pertinent for performance purposes, we cannot negligence resource consumption and consequently the *cost* metric. When analyzing *cost*, the gains of LT_{ce} are not so evident in Figure 7 (b). However, this strategy also obtained the best mean of all loads costs.

Aiming at generating a single approach to guide



(a) Execution Time

(b) Cost

Figure 7: Results of metrics (a) *time* and (b) *cost* when running the load patterns.

the functioning of the Live Thresholding technique, we used the *cost* within the Weighted Sum Model (Triantaphyllou, 2000) techique. Therefore, for each load pattern we classified the *cost* results of the nine combinations of LT_{xy} in an ascending fashion. For each one we attributed a weight starting from 1.0 for the first place, 0.9 for the second, 0.8 for the third and so on. Thus, considering we have executed all nine *LT* combinations with four load patterns, each LT_{xy} received four weights. So then, the sum of them represents the final result where the highest value defines the final approach for *LT*. Table 1 shows this evaluation revealing LT_{ce} as the better strategy for *LT*.

Table 1: Using the cost metric to define the final solution for the Live Thresholding: LT_{ce} was selected as the best approach when combining different types of work loads.

LT_{xy}	Weight				
	Ascending	Constant	Descending	Wave	Total
LT_{ad}	0.3	0.7	0.8	0.8	2.6
LT_{ae}	0.9	0.8	0.6	0.7	3.0
LT_{af}	0.5	0.9	0.5	1.0	2.9
LT_{bd}	0.2	0.4	0.3	0.4	1.3
LT_{be}	0.6	0.3	0.2	0.5	1.6
LT_{bf}	0.7	0.6	0.4	0.3	2.0
LT_{cd}	0.4	0.2	1.0	0.6	2.2
LT_{ce}	1.0	1.0	0.9	0.2	**3.1**
LT_{cf}	0.8	0.5	0.7	0.9	2.9

5.3 Performance Analysis

Table 2 shows results we obtained running the application with all load patterns and parameters. For the scenario s2, the results regards to the strategy LT_{ce} which is the one we adopted as final in Subsection 5.2. For simplicity, here we will call LT_{ce} just *LT*. One of the differences between *LT* and approaches with static thresholds regards to how each strategy behaviors at the exact moment after a resource reorganization. In the best case for static thresholds, lower values for t_u and higher values for t_l increases reactivity. In these cases, when the load drops or increases after an operation it can stay over or under the same threshold that has triggered the last operation. For this reason, a new operation can occur sooner and it can anticipate actions. Conversely, in the worst case, higher values for t_u and lower values for t_l decreases reactivity since the load could stagnate between the thresholds not allowing more operations. In addition, with loads trending up or down, in these situations after an operation it could take more time to the load reach a threshold again. Differently from static thresholds, *LT* proposes an algorithm to recalculate both t_u and t_l after an elasticity operation to close the load after the operation. Thus, elasticity actions do not occur in the observation that the thresholds are recalculated. It takes some more observations do continue adapting the thresholds and then violate it again. In most results, this distinct behavior made *LT* achieve *time* and *cost* values slightly higher then the ones the better set of static thresholds achieved. On the other hand, it also made *LT* achieve results much better than the ones obtained by the worst set of thresholds.

Table 2: Results of all scenarios and metrics.

Scenario	Application Pattern	Thresholds t_u	Thresholds t_l	Time	Resource	Cost
s1 Without Elasticity	Ascending	-	-	4319	8618	37221142
	Descending	-	-	4410	8798	38799180
	Constant	-	-	4283	8542	36585386
	Wave	-	-	4363	8700	37958100
	Pos. Exponential	-	-	4601	9180	42237180
	Neg. Exponential	-	-	4528	9042	40942176
	All Random	-	-	4018	8040	32304720
	Partial Random	-	-	3994	8010	31991940
s2 Live Thresholding	Ascending	-	-	1769	12064	21341216
	Descending	-	-	2000	13088	26176000
	Constant	-	-	1932	12828	24783696
	Wave	-	-	2165	13408	29028320
	Pos. Exponential	-	-	1918	10138	19444684
	Neg. Exponential	-	-	2089	11134	23258926
	All Random	-	-	1829	11920	21801680
	Partial Random	-	-	2036	10770	21927720
s3 Static Thresholds	Ascending	70	30	1818	11936	21699648
			50	1825	11874	21670050
		90	30	3091	9450	29209950
			50	3000	9540	28620000
	Descending	70	30	1891	14056	26579896
			50	1880	12746	23962480
		90	30	2667	10110	26963370
			50	2638	9840	25957920
	Constant	70	30	1888	12382	23377216
			50	1913	12546	24000498
		90	30	2625	9886	25950750
			50	2653	9954	26407962
	Wave	70	30	2286	12496	28565856
			50	2296	11784	27056064
		90	30	2911	9750	28382250
			50	2904	9600	27878400
	Pos. Exponential	70	30	1880	9600	18048000
			50	1888	10440	19710720
		90	30	2212	9790	21655480
			50	2226	9816	21850416
	Neg. Exponential	70	30	2018	12090	24397620
			50	2042	11810	24116020
		90	30	2093	11250	23546250
			50	2072	10664	22095808
	All Random	70	30	1782	11700	20849400
			50	1799	11730	21102270
		90	30	2534	9120	23110080
			50	2484	9270	23026680
	Partial Random	70	30	1757	11490	20187930
			50	1754	11430	20048220
		90	30	2861	8850	25319850
			50	2727	8910	24297570

6 CONCLUSION

This article presented the SelfElastic model as an advance in the current state of research by offering the aforementioned features both in terms of application and parameter writing. SelfElastic offers hybrid elasticity through the Live Thresholding technique, so self-organizing threshold values and resource allocation to offer a competitive solution at performance and cost levels. Although being developed for parallel applications, SelfElastic can be easily extended to address elasticity adaptivity on Web-based services including e-commerce and electronic funds transfer. The results are encouraging in favor of using Live Thresholding since LT presents performance and costs very close or even better than static thresholds.

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