Statistical Modeling of Spot Instance Prices in Public Cloud Environments

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***Abstract*—The surge in demand for utilizing public Cloud resources has introduced many trade-offs between price, performance and recently reliability. Amazon's Spot Instances (SIs) create a competitive bidding option for the public Cloud users at lower prices without providing reliability on services. It is generally believed that SIs reduce monetary cost to the Cloud users, however it appears from the literature that their characteristics have not been explored and reported. We believe that characterization of SIs is fundamental in the design of stochastic scheduling algorithms and fault tolerant mechanisms in public Cloud environments for spot market. In this paper, we have done a comprehensive analysis of SIs based on one year price history in four data centers of Amazon's EC2. For this purpose, we have analyzed all different types of SIs in terms of spot price and the inter-price time (time between price changes) and determined the time dynamics for spot price in hour-in-day and day-of-week. Moreover, we have proposed a statistical model that fits well these two data series. The results reveal that we are able to model spot price dynamics as well as the inter-price time of each SI by the mixture of Gaussians distribution with three or four components. The proposed model is validated through extensive simulations, which demonstrate that our model exhibits a good degree of accuracy under realistic working conditions.**

***Keywords*-Cloud Computing; Spot Price; Statistical Model;**

I. Introduction

Due to the surge in demand for using utility computing systems like public Cloud resources, many trade-offs between price and performance have emerged. One particular type of Cloud service, which is known as Infrastructure-as-as-Service (IaaS) provides raw computing with different capacity and storage in the form of Virtual Machines (VMs) with various prices on a pay-as-you-go basis. For instance, Amazon provides on-demand and reserved VM instances, which are associated with a fixed set price [13]. However, Amazon can increase or decrease these prices based on their own local policy. There are 64 different types of instances with various capacities and prices under two operating systems (i.e. 32 for Linux and 32 for Windows) which are made available by Amazon in four data centers as illustrated in Table I (sorted by their prices). In this Table, the prices are given for Linux operating system and the instances labeled with 'm1', 'm2', and 'c1' are standard, high-memory, and high-CPU instances, respectively.

In December 2009, Amazon released a new type of instances called Spot Instance (SI) to sell the idle time of Amazon's EC2 data centers [3]. The price of an SI, *spot price*, depends on the type of instance as well as VM demand within each data center. In fact, spot instances are an alternative to other two classes of instances which offer a low price but less reliable and competitive bidding option for the public Cloud users. Therefore, another aspect, *reliability*, has been added to the existing trade-offs to make utility computing systems more challenging than ever.

In order to utilize SIs, the Cloud users provide a *bid* which is the maximum price to be paid for an hour of usage. Whenever the current price of an SI is equal or less than the user bid, the instance is made available to the user. If the price of an SI becomes higher than the user's bid, *out-of-bid* event (failure), the VM(s) will be terminated by Amazon automatically and user does not pay for any partial hour. However, if the user terminates the running VM(s), she has to pay for the full hour. Amazon charges users per hour by the market price of the SI at the time of VM creation.

There are a limited number of works on how to utilize SIs to decrease the monetary cost of utility computing for Cloud users [12], [14]. However, a thorough statistical analysis and modeling of SIs have not been appeared in the literature, the focus of our research in this study. In this paper, we provide a comprehensive analysis of all SIs in terms of spot price and the inter-price time (time between price changes) in four Amazon's data centers (i.e. us-west, us-east, eu-west, and ap-southeast). Moreover, we propose a statistical model to capture the volatile spot prices in Amazon's data centers. The main contributions of this paper are as follows:

- We provide statistical analysis for all SIs in Amazon's EC2 data centers. We also determine the time correlation in spot price in terms of hour-in-day and day-of-week.
- We model spot price and the inter-price time of each SI with the mixture of Gaussians distribution. A model calibration algorithm is also proposed to deal with an observed price trend in the real price history.
- We validate and verify the accuracy of our proposed model through simulation under realistic working conditions.

TABLE I
PRICES OF ON-DEMAND INSTANCES IN DIFFERENT DATA CENTERS OF AMAZON (PRICES GIVEN IN CENTS).

Instances	us-west	us-east	eu-west	ap-southeast	EC2 Compute Unit	Memory (GB)	Storage (GB)
m1.small	9.5	8.5	9.5	9.5	1	1.7	160
c1.medium	19	17	19	19	5	1.7	350
m1.large	38	34	38	38	4	7.5	850
m2.xlarge	57	50	57	57	6.5	17.1	420
m1.xlarge	76	68	76	76	8	15	1690
c1.xlarge	76	68	76	76	20	7	1690
m2.2xlarge	114	100	14	114	13	34.2	850
m2.4xlarge	228	200	228	228	26	68.4	1690

We believe that results of this research would significantly helpful in the design of stochastic scheduling algorithms and fault tolerant mechanisms (e.g. checkpointing and replication algorithms) for spot market in public Cloud environments. Moreover, this model can be used by other IaaS Cloud providers that look forward to offer such a service in the near future.

The paper is structured as follows. In Section II, we describe the processes that we model in this paper. We discuss related work in Section III. We examine the pattern of spot price in Section IV. In Section V, we present the global statistics for all SIs. We then illustrate distribution fitting for spot price and the inter-price time in Section VI. In Section VII, we propose an algorithm for model calibration. We discuss the validation of the proposed models through simulation in Section VIII. In Section IX, we summarize our contributions and describe future directions.

II. Modeling Approach

In this section, we describe two variables that we are going to analyze and model. In Amazon's data centers, SIs have two variables (i.e. spot price and inter-price time) specified by the Cloud provider and one variable (user's bid) determined by users. In this study, we focus on the analysis and modeling of spot price and the inter-price time as two highly volatile system variables. These variables are illustrated in Figure 1 where P_i is the price of an SI at time t_i. So, the inter-price time is defined as $T_i = t_{i+1} - t_i$. Therefore, the time series of spot price (P_i) and the inter-price time (T_i) are analyzed and modeled in the following sections.

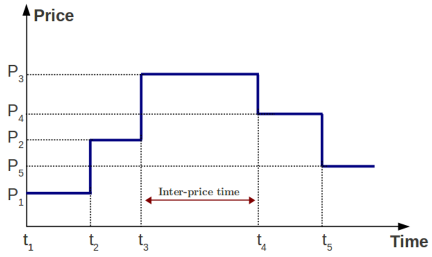


Fig. 1. Spot price and the inter-price time of Spot instances.

The traces that we use in this study are one year price history of all Amazon SIs from the first of February 2010 to mid-February 2011. We use the first 10-month (Feb-2010 to Nov-2010) in the modeling process. These 10-month traces along with the last 2-month are used for the model validation purpose. The spot price history is freely provided by Amazon per SI for each data center and also available through other third-parties such as [1]. We do not use data prior to February 2010 due to an algorithm issue reported in [2] for prices. Moreover, we only use the SIs with Linux operating systems from all data centers. Due to space limitation as well as similarity of the results, we present our findings for only one data center (i.e. eu-west). Interested readers can refer to the extended version of this paper [9] for more discussions about other data centers.

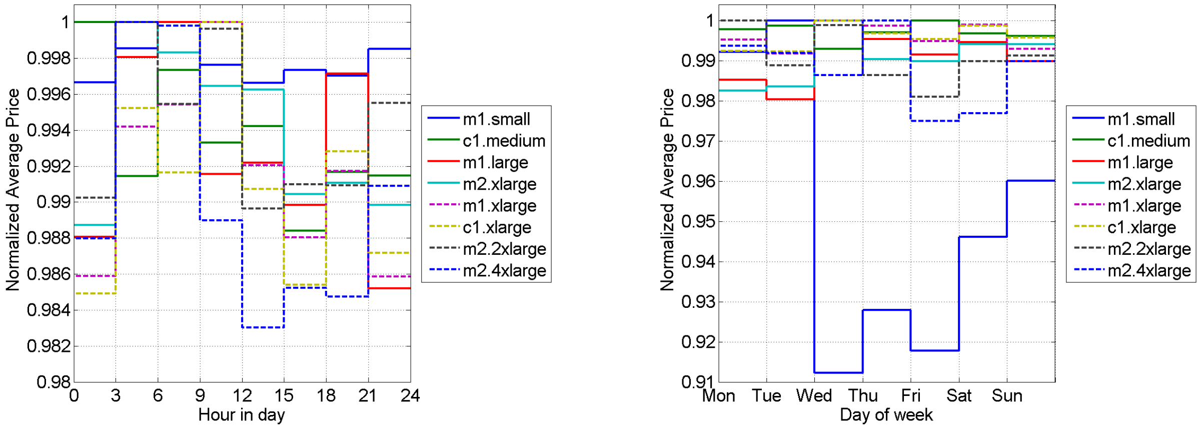
III. Related Work

To the best of our knowledge, this is the first work to analyze and model spot instances in public Cloud environments. However, there are some papers which investigated the usage of SIs to decrease the monetary cost of utility computing.

Yi *et al.* [14] introduced some checkpointing mechanisms for reducing cost of SIs. They used the real price history of EC2 spot instances and showed how the adaptive checkpointing schemes could decrease the monetary cost and improve the job completion times. In [4], a decision model for the optimization of performance, cost and reliability under SLA constraints while using SIs is proposed. They used the real price history and workload models to demonstrate how their proposed model can be used to bid optimally on SIs to reach different objective with desired levels of confidences.

Chohan *et al.* in [6] proposed a method to utilize the SIs to speed up the MapReduce tasks. They provided a Markov chain to predict the expected lifetime of an SI. They concluded that having a fault tolerant mechanism is essential to run MapReduce jobs on SIs. Also, in [12], authors proposed a hybrid Cloud architecture to lease the SIs to manage peak loads of a local cluster. They proposed some provisioning policies and investigated the utilization of SIs compared to on-demand instances in terms of monetary cost saving and number of deadline violations.

Although the current literature shows that SIs are good alternative for on-demand or reserve instances in terms of monetary cost, the characteristics of SIs are not clear to users and researchers in the community. Hence, for this research we propose to devise a statistical model for SIs for better understanding of the price mechanisms in Amazon's data centers.



(a) Hour-in-day

(b) Day-of-week

Fig. 2. Patterns of spot price in eu-west data center.

IV. Patterns of Spot Price

In this section, we examine hour-in-day and day-of-week time dynamics for the price of different SIs in eu-west data center. We use the same approach as [11] to show how the price of one SI changes each hour in the day or each day of the week. As we have the price history in GMT time zone, we adjusted the local time for the time zone. This adjustment could reveal the dependency of spot price on the local time of a data center. In Figure 2(a), we create eight 3-hour time slots per day, and determine the average price of each SI in each time slot over all days. Then, we normalized this average by the maximum average price over all days. Note that the frequency of 3-hour sampling could be increased to 1-hour sampling with 24 time slots in a day. However, it would only increase the sample size without shedding much light on the price dynamics, since spot price in Amazon's data centers are changing at the earliest every 2-3 hours (see Section V).

In Figure 2(b), we applied the same procedure to obtain the average price over seven 24-hours time slots within a week. In Figure 2(a), we can see that the y-axis is in the range of [0.98 1.0] where there is an increasing trend over the first-half of each day ([0 12]) and decreasing trend in spot price during the second-half of each day for all SIs in this data center.

The y-axis in Figure 2(b) has wider range of [0.91 1.0] for eu-west data center[1]. As it is observable from this plot, we can not find any specific pattern for spot price, except the decreasing in prices on weekends. However, for other Amazon's data centers, we see more clear patterns in day of the week where on Tuesday we have the maximum price for almost all SIs in those data centers. Moreover, the lowest price are on Saturday, but on Sunday we again observe the increasing in price for all SIs. These facts are more pronounced in us-east and ap-southeast data centers [9].

V. Global Statistics and Analysis

In the following, we analyze the price history of different SIs in eu-west data center. We inspect the basic statistics of the traces in terms of spot price in Table II; and in terms of the inter-price time in Table III. The statistics in the tables are mean, trimmed mean (the mean value after discarding 10% of extreme values), median, standard deviation (Std), coefficient of variance (CV), interquartile range (IQR), maximum, minimum, skewness (the third moment), kurtosis (the forth moment) and number of samples.

These tables show three types of descriptive statistics. Statistics of the first type (mean, median, trimmed mean) reveal the central tendency of the distributions. Statistics of the second type (CV, IQR, minimum, maximum) reflect the spread of the distributions. Statistics of the third type (kurtosis, skewness) represent the shape of the distributions.

First of all, we find that on average the price of SIs can be as low as 44% of on-demand instances (this percentage is 38%, for us-east data center which is the cheapest data center). This expresses that there are some opportunities in reducing monetary cost of utility computing at the cost of unreliability. Moreover, the maximum price of some SIs (like m1.large) is bigger than the price of corresponding on-demand instance (specially in us-east data center). Thus, even if the users' bid is as high as the on-demand prices, we may still have a probability of out-of-bid events.

The results in these tables reveal that the ratios between the mean and the median for spot price and the inter-price time of SIs are close to 1 for each trace. This indicates that Gaussian distribution might be a good option for the model. However, the skewness and kurtosis values show that the underlying distributions are right-skewed and short-tailed. Therefore, Gaussian distribution may not be a representative model to use and a better distribution is in order.

[1] For other data centers, this range is narrower ([0.95 1.0]).

TABLE II
Statistics for spot price in eu-west data center (Values given in cents).

Instances	Mean	TrMean	Median	Std	CV	IQR	Max	Min	Skewness	Kurtosis	No.
m1.small	4.00	4.00	4.00	0.19	0.05	0.20	9.50	3.80	9.44	242.97	3702
c1.medium	8.00	8.00	8.00	0.27	0.03	0.40	10.10	7.60	0.28	3.91	3812
m1.large	16.04	16.02	16.10	0.85	0.05	1.00	50.00	15.20	21.55	792.41	3875
m2.xlarge	24.04	24.03	24.10	1.03	0.04	1.40	57.10	22.80	12.91	387.69	3763
m1.xlarge	32.05	32.01	32.10	1.60	0.05	2.00	76.00	30.40	15.34	415.47	3917
c1.xlarge	32.04	32.03	32.10	1.07	0.03	2.00	45.00	30.40	0.54	8.27	3658
m2.2xlarge	56.04	56.04	56.20	1.83	0.03	3.42	76.00	53.20	0.25	4.99	4001
m2.4xlarge	112.08	112.08	112.50	3.62	0.03	6.80	150.00	106.40	0.21	4.55	3912

TABLE III
Statistics for the inter-price time in eu-west data center (Values given in hours).

Instances	Mean	TrMean	Median	Std	CV	IQR	Max	Min	Skewness	Kurtosis	No.
m1.small	1.96	1.61	1.35	2.66	1.35	0.30	109.08	0.02	19.94	727.54	3701
c1.medium	1.91	1.59	1.34	1.86	0.97	0.32	22.81	0.02	4.53	30.63	3811
m1.large	1.88	1.57	1.33	1.79	0.95	0.31	30.94	0.02	5.02	42.02	3874
m2.xlarge	1.79	1.53	1.34	1.56	0.87	0.30	22.83	0.02	4.93	38.54	3762
m1.xlarge	1.86	1.58	1.34	1.78	0.96	0.31	38.20	0.02	7.34	101.43	3916
c1.xlarge	1.99	1.56	1.34	7.22	3.63	0.30	378.19	0.02	44.38	2169.40	3657
m2.2xlarge	1.82	1.55	1.33	1.60	0.88	0.31	29.02	0.02	5.11	45.75	4000
m2.4xlarge	1.86	1.58	1.34	1.71	0.92	0.31	26.51	0.02	5.20	44.28	3911

Additionally, we can observe that the inter-price time is more variable than spot price due to higher values of coefficient of variance. Also, analysis of the trimmed mean confirmed that inter-price time has greater variability. Therefore, we may need distributions with higher degrees of freedom, to model the inter-price time for these traces. It is worth noting that the minimum inter-price time is almost one hour in all data centers except eu-west which is about a few minutes and can be seen in Table III). Moreover, in eu-west data center, the set price of SIs are stable on average for less than two hours, where for other data centers this duration is about 2-3 hours [9]. This is the justification of 3-hour time slots to examine patterns of spot price in Figure 2(a).

VI. Distribution Fitting

After global statistical analysis, we first inspect the Probability Density Function (PDF) of spot price and the inter-price time. Then, we conduct parameter fitting for the Mixture of Gaussians (MoG) distribution by the expectation maximization (EM) algorithm to model both time series. We considered other distributions, such as Weibull, Normal, Log-normal and Gamma distributions as well. However, the mixture of Gaussians distribution shows the better fit with respect to others [9].

A. Probability Densities

The PDFs of spot price of each SI in eu-west data center are depicted in Figure 3. We can easily observe *bi-modality* in the probability density functions. Moreover, the price distribution of all SIs, except m1.small, are almost symmetric. The exception for m1.small is possibly because of diverse usage patterns of this instance as the cheapest resource in each data center.

The PDFs of the inter-price time for each SI in eu-west are represented in Figure 4. Obviously, there is a single dominant mode (peak) in the density functions when compared to (nearly) equal peaks in the PDFs of spot price. Most of SIs have the peak around two hours, which confirm the results of the previous section (see Mean column in Table III). The reason for the very sharp peak in these density functions is investigated in Section VII. Observation from the plotted density functions of both time series, our decision to propose a mixture of Gaussians distribution as a good candidate for approximating such density shapes is further strengthened.

B. Parameter Estimation and Goodness of Fit Tests

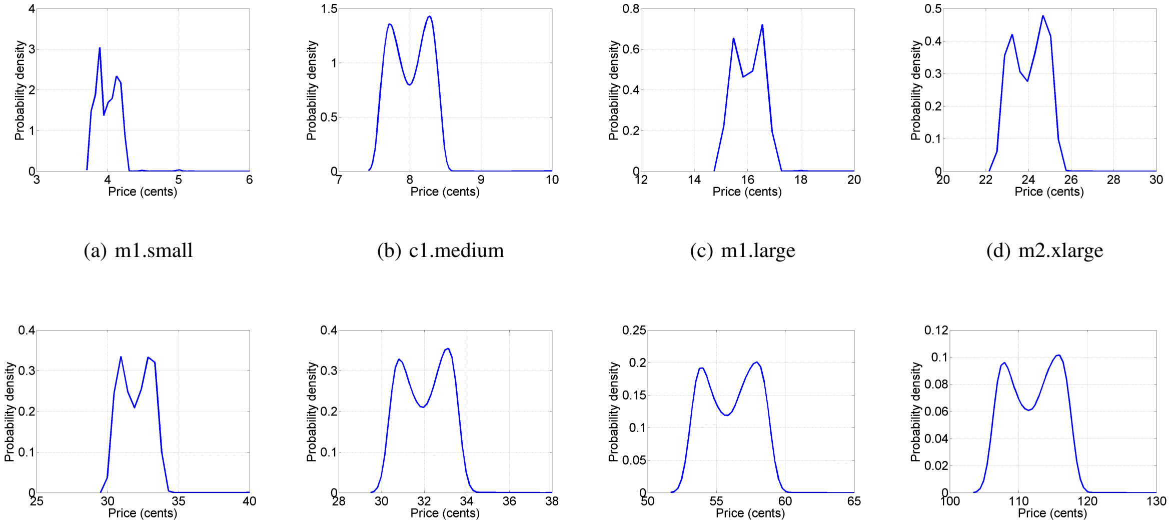
In this section, we conduct parameter fitting for the mixture of Gaussians distribution with k components, which is defined as follows:

$$cdf(x; k, \vec{p}, \vec{\mu}, \vec{\sigma^2}) = \sum_{i=1}^{k} \frac{p_i}{2} \left(1 + erf(\frac{x - \mu_i}{\sigma_i \sqrt{2}}) \right) \qquad (1)$$

where $\vec{\mu}$, $\vec{\sigma^2}$, and $\vec{p}$ are the vector of mean, variance and probability of components with k items. Also, $erf()$ is the error function, which is defined as follows:

$$erf(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt \qquad (2)$$

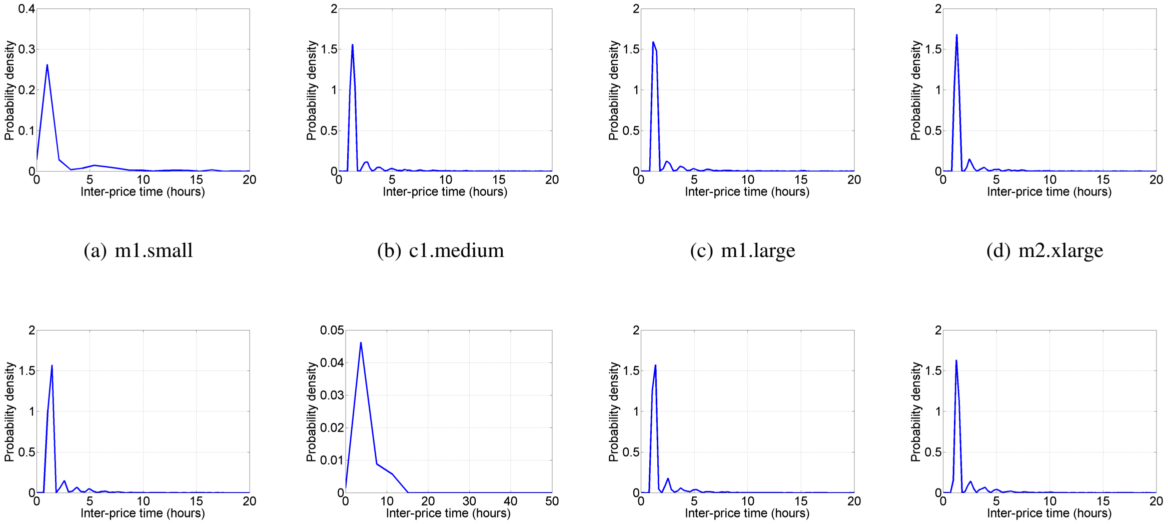
To maximize the data likelihood in terms of parameters $\vec{\mu}$ and $\vec{\sigma^2}$ where k is given a priori, we adopt the expectation maximization (EM) algorithm, which is a general maximum likelihood estimation. Parameter fitting was done using Model Based Clustering (MBC), which is introduced by Fraley and Raftery [7]. MBC is a methodological framework that can be used for data clustering as well as (multi)variate density estimation. One assumption is that data has several components each of which is generated by a probability distribution. Model Based Clustering uses Bayesian model selection to choose the best model in terms of number of components. In contrast, we



(a) m1.small (b) c1.medium (c) m1.large (d) m2.xlarge

(e) m1.xlarge (f) c1.xlarge (g) m2.2xlarge (h) m2.4xlarge

Fig. 3. Probability density functions of spot price for all SIs in eu-west data center.



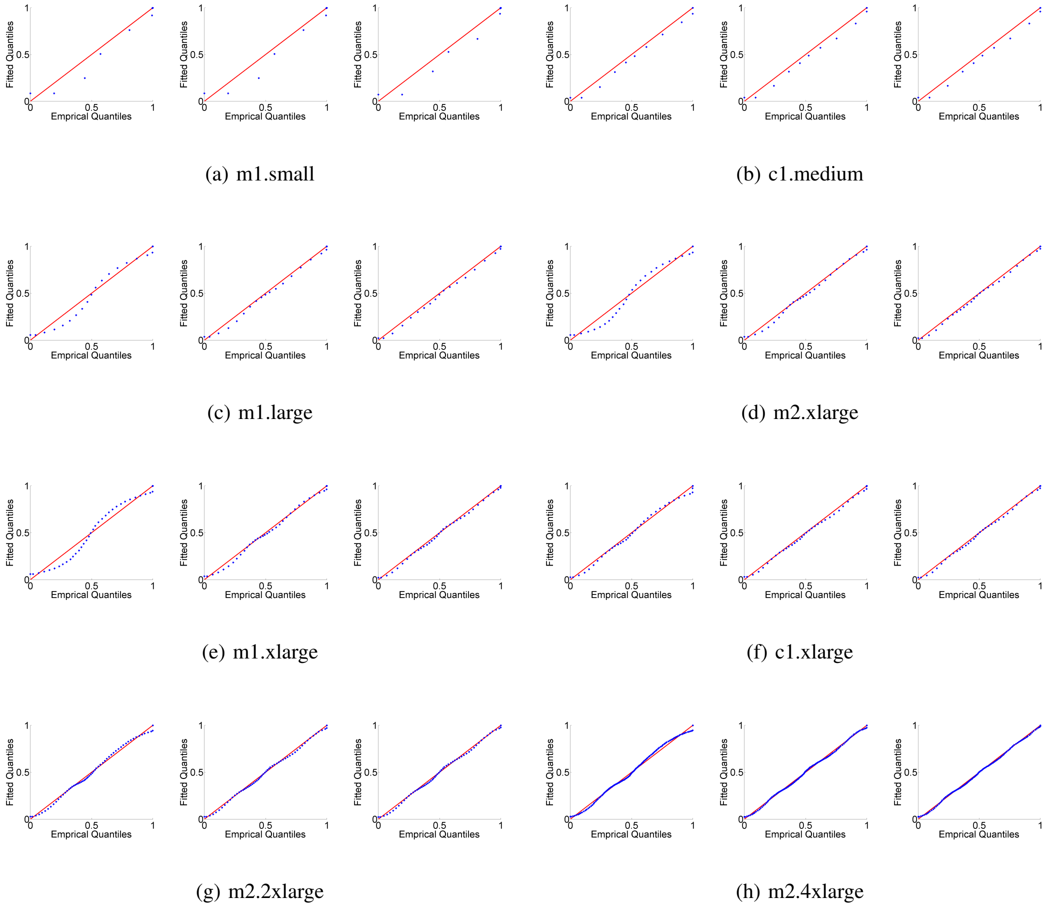
(a) m1.small (b) c1.medium (c) m1.large (d) m2.xlarge

(e) m1.xlarge (f) c1.xlarge (g) m2.2xlarge (h) m2.4xlarge

Fig. 4. Probability density functions of the inter-price time for all SIs in eu-west data center.

use the goodness of fit (GOF) tests to determine the best model as we have an estimation for the number of components in the model. We choose the number of components between 2 and 4 ($2 \leq k \leq 4$) based on the observation of the density functions. We measured the goodness of fit of the resulting models using a visual method (i.e. standard probability-probability (PP) plots) and Kolmogorov-Smirnov (KS) and Anderson-Darling (AD) tests as quantitative metrics.

After parameter estimation, we must examine the quality of each fit through GOF tests. First of all, we present the graphical results of distribution fitting for spot price and the inter-price time of all SIs in Figure 5 and Figure 6 for eu-west data center, respectively. In these plots, the closer the plots are to the line $y = x$, the better the fit. In each plot x-axis is the empirical quantiles while y-axis is the fitted quantiles. Based on these figures, the mixture of Gaussians distribution with three or four components can fit spot price and the inter-price time of SIs in eu-west data center. The only instance which is hard to fit, specially in terms of spot price, is m1.small instance.



(a) m1.small

(b) c1.medium

(c) m1.large

(d) m2.xlarge

(e) m1.xlarge

(f) c1.xlarge

(g) m2.2xlarge

(h) m2.4xlarge

Fig. 5. PP-plots of spot price in eu-west for mixture of Gaussians ($k = 2, k = 3, k = 4$). X-axis: empirical quantiles, and Y-axis: fitted quantiles.

To be more quantitative, we also report the p-values of two GOF tests (i.e. KS and AD tests). We randomly select a subsample of 50 of each trace and compute the p-values iteratively for 1000 times and finally obtain the average p-value. This method is similar to the one used by the authors in [10].

The results of GOF tests are listed in Table IV and Table V for spot price and the inter-price time in eu-west, respectively. Moreover, in each row the best fits are highlighted. In some cases, we have two winners as there is one best fit per each GOF test. These quantitative results strongly confirm the graphical results of the PP-plots. The p-values in the first row of Table IV express that spot price of m1.small instance is hard to fit, even with four components. This is the case for other data centers as well, specially for us-east data center [9].

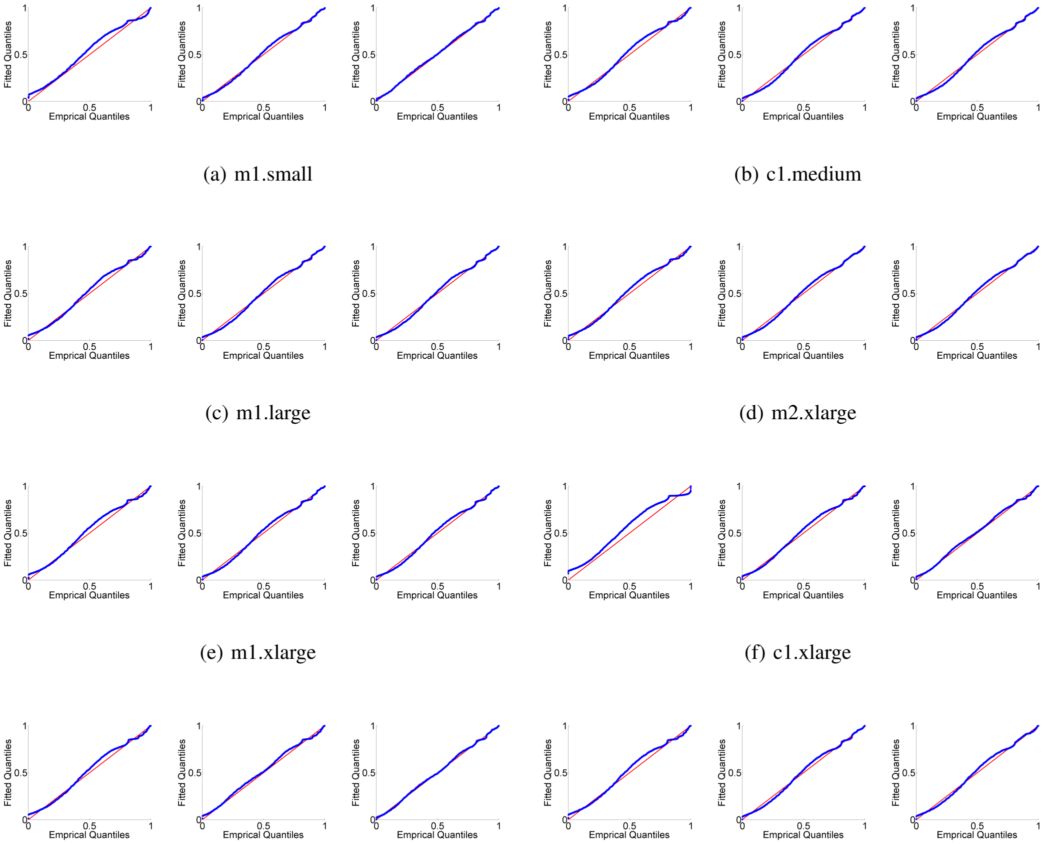
TABLE IV
P-VALUES RESULTING FROM KS AND AD TESTS FOR SPOT PRICE.

Instances	**MoG** ($k = 2$)	**MoG** ($k = 3$)	**MoG** ($k = 4$)
m1.small	0.016 0.791	0.017 0.789	0.053 0.803
c1.medium	0.211 0.779	0.217 0.791	0.224 0.790
m1.large	0.113 0.678	0.319 0.752	0.354 0.754
m2.xlarge	0.139 0.616	0.356 0.721	0.415 0.734
m1.xlarge	0.134 0.570	0.369 0.708	0.431 0.706
c1.xlarge	0.394 0.681	0.444 0.705	0.421 0.707
m2.2xlarge	0.420 0.648	0.469 0.682	0.450 0.672
m2.4xlarge	0.429 0.617	0.463 0.637	0.476 0.653

As the number of parameters in the MoG distribution is $3k + 1$ (see Equation 1), so we have a trade-off between accuracy and complexity of the model. With fewer components, the analysis becomes simpler that gives reasonably good fit to spot price and inter-price time with a compromise of accuracy to some extent. This would significanly help in understanding the data series on the first step. With this understanding a model to better fit the data series with many components can be designed. Hence, for the sake of simplicity and homogeneity, in the rest of this paper we choose the model with three components ($k = 3$) for both spot price and the inter-price time for further analysis. The set of parameters for MoG distributions for spot price and the inter-price time for $2 \leq k \leq 4$ in all data centers are reported in [9].

VII. Model Calibration

In this section, we look into the time evolution of spot price and the inter-price time, which potentially can lead us to obtain a more accurate model. For this purpose, we examine the scatter plot of spot price and the inter-price time during



(a) m1.small

(b) c1.medium

(c) m1.large

(d) m2.xlarge

(e) m1.xlarge

(f) c1.xlarge

(g) m2.2xlarge

(h) m2.4xlarge

Fig. 6. PP-plots of the inter-price time in eu-west for mixture of Gaussians ($k = 2, k = 3$, $k = 4$). X-axis: empirical quantiles, and Y-axis: fitted quantiles.

Algorithm 1: Model Calibration Algorithm

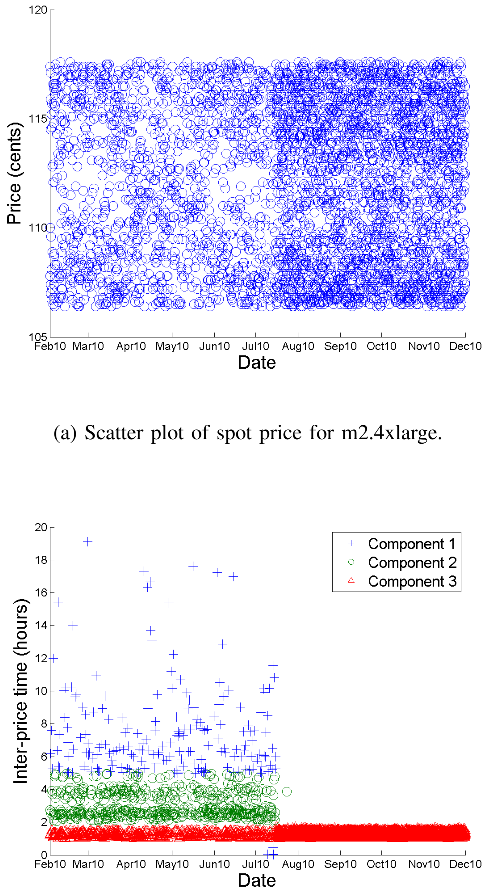
```
**Input**: $Trace_{inst}, k$
**Output**: $CalDate, \overrightarrow{RCmps}$
$T_s \leftarrow Trace_{inst}.start.time$;
$T_e \leftarrow Trace_{inst}.end.time$;
$n \leftarrow Sizeof(Trace_{inst})$;
$\overrightarrow{index} \leftarrow (c_1, c_2, \dots, c_n) \quad c_i \in \{1, \dots, k\}$;
$\overrightarrow{date} \leftarrow (d_1, d_2, \dots, d_n) \quad d_i \in \{T_s \dots T_e\}$;
$q_{a,b} \leftarrow$ probability of component $a$ in month $b$;
$\overrightarrow{Q} \leftarrow \{q_{a,b} | a \in \{1, \dots, k\}, b \in \{T_s \dots T_e\}\}$;
$\overrightarrow{Q_m} \leftarrow \{q_{f,e} | q_{f,e} < q_0, q_{f,e} \in \overrightarrow{Q}\}$;
$\overrightarrow{Cmps} \leftarrow \{g | q_{g,h} \in \overrightarrow{Q_m}\}$;
$\overrightarrow{RCmps} \leftarrow \{1, \dots, k\} - \overrightarrow{Cmps}$ ;
$m \leftarrow min\{h | q_{g,h} \in \overrightarrow{Q_m}\}$;
$//Trace_{inst}(m)$ is the trace for month $m$;
$T_{m_s} \leftarrow Trace_{inst}(m).start.time$;
$T_{m_e} \leftarrow Trace_{inst}(m).end.time$;
$z \leftarrow Sizeof(Trace_{inst}(m))$;
$\overrightarrow{Sindex} \leftarrow (c'_1, c'_2, \dots, c'_z) \quad c'_i \in \{1, \dots, k\}$;
$\overrightarrow{Sdate} \leftarrow (d'_1, d'_2, \dots, d'_z) \quad d'_i \in \{T_{m_s} \dots T_{m_e}\}$;
$t \leftarrow max\{r_l | \overrightarrow{Sindex}(r_l) == g, l \in \{1, \dots, z\}\}$;
$CalDate \leftarrow \overrightarrow{Sdate}(t)$;
```

TABLE V
P-VALUES RESULTING FROM KS AND AD TESTS FOR THE INTER-PRICE.

Instances	**MoG** ($k = 2$)	**MoG** ($k = 3$)	**MoG** ($k = 4$)
m1.small	0.347 0.476	0.415 0.592	0.489 0.627
c1.medium	0.382 0.546	0.390 0.566	0.380 0.566
m1.large	0.390 0.552	0.387 0.573	0.400 0.574
m2.xlarge	0.389 0.556	0.393 0.566	0.405 0.585
m1.xlarge	0.369 0.526	0.391 0.564	0.406 0.581
c1.xlarge	0.221 0.319	0.399 0.561	0.467 0.602
m2.2xlarge	0.376 0.532	0.426 0.570	0.463 0.610
m2.4xlarge	0.368 0.529	0.383 0.569	0.395 0.573

February 2010 till November 2010. Due to space limitation, we just present the plots for m2.4xlarge instance. The results are consistent for other instance types within the data center.

Figure 7(a) depicts the scatter plot of spot price for m2.4xlarge in eu-west data center for the duration of the price history. As it can be seen in this figure, there is no clear correlation in spot price where they are evenly distributed in a specific range (this range depends on the type of instances). However, congestion of spot price is increased after mid-July and this is the case for all SIs in eu-west data center. To confirm this observation, we examine the scatter plot of the inter-price time for this SI in Figure 7(b). We observe that



(a) Scatter plot of spot price for m2.4xlarge.

(b) Scatter plot along with the components' distribution of the inter-price time for m2.4xlarge.

Fig. 7. Scatter plot of spot price and the inter-price time for m2.4xlarge.

inter-price time become suddenly shorter after mid-July. That means, the frequency of changing price is increased while spot price remains bounded within a small price range. The inspection of other SIs within the data center reveals the same result. This is also the reason of very sharp peak in density functions of the inter-price time in Figure 4.

This trend is possibly due to some fine tunings made by Amazon in their pricing algorithm. It is worth noting that the same issue has been observed in other Amazon's EC2 data centers in different dates. In us-east it happened in August 2010, and in us-west and ap-southeast in January 2011 (Figures are plotted in [9]).

Focusing on the scatter plot of the inter-price time (MoG model for $k = 3$) presented in Figure 7(b), we can see that after mid-July only one component (i.e. component 3) remains and other components collapsed to a small band. As this observation is consistent over all SIs, we propose a model calibration algorithm (Algorithm 1) to find the date of collapsing (which is called calibration date) as well as remaining component(s).

TABLE VI
THE RESULTS OF MODEL CALIBRATION IN EU-WEST ($k = 3$).

Instances	Calibration Dates	Remaining Components
m1.small	24-July	3
c1.medium	15-July	1
m1.large	15-July	3
m2.xlarge	13-July	1
m1.xlarge	23-July	1
c1.xlarge	23-July	1
m2.2xlarge	23-July	1,2
m2.4xlarge	15-July	3

The algorithm needs the trace of the inter-price time of an SI ($Trace_{inst}$) and the number of components (k). The result of mixture of Gaussians model with k components is $\overrightarrow{index}$. Also, $\overrightarrow{date}$ is a vector, each element of which correspond to each item of $\overrightarrow{index}$. At first, the algorithm computes the probability of each component in each month in the whole trace and after that finds a list ($\overrightarrow{Q_m}$) where the probability of one or more components is less than q_0 (line 4-8). q_0 is a threshold value and we define it as low as 0.01 (i.e. $q_0 = 0.01$). The components that are not in this list are remaining components ($\overrightarrow{RCmps}$ in line 10). The first month in the list of $\overrightarrow{Q_m}$ is the calibration month, called m (line 11). Finally, the last occurrence of the component(s) in month m would be the calibration date ($CalDate$), which is obtained in line 13-19.

The results of applying this algorithm for all SIs in eu-west data center are presented in Table VI where all calibration dates are in July. Moreover, for all SIs, except m2.2xlarge, only one out of three components remains after the calibration date.

The last step of the model calibration is probability adjustment where the probability of remaining component(s) must be scaled up to one. This adjustment can be done by the following formula:

$$p_j = \frac{p_j}{\sum\limits_{\forall i} p_i} \quad i, j \in \overrightarrow{RCmps} \tag{3}$$

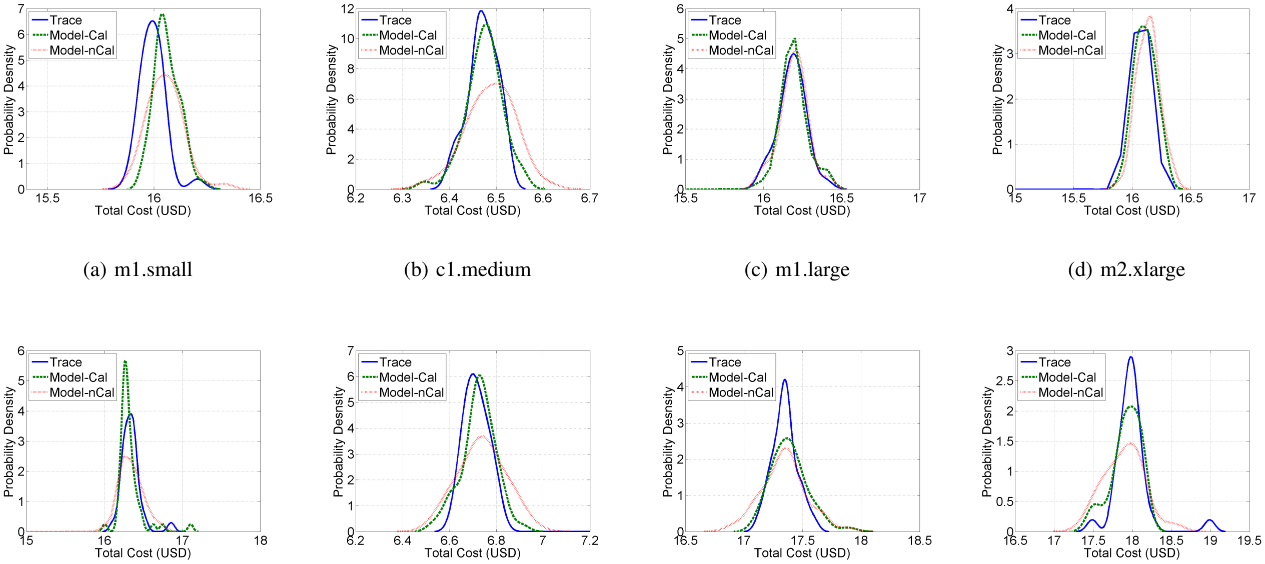
In other words, in the calibrated model for each SI, we just change the probability of remaining component(s) after the calibration date. In the following section, we investigate the accuracy of the calibrated model with respect to the real price history as well as the non-calibrated model.

VIII. Model Validation

In order to validate the proposed model, we implemented a discrete event simulator using CloudSim [5]. The simulator uses the model or the price history traces to run the input workload. We consider the case where the user requests for one VM from one type of SI and runs whole jobs on that VM. The total monetary cost of running the workload on an SI is the parameter to be considered.

A. Simulation Setup

The workload that we use in our experiments is the workload traces from LCG Grid which is taken from the Grid



(a) m1.small

(b) c1.medium

(c) m1.large

(d) m2.xlarge

(e) m1.xlarge

(f) c1.xlarge

(g) m2.2xlarge

(h) m2.4xlarge

Fig. 8. Model validation for all SIs in eu-west for the modeling traces (Feb-2010 to Nov-2010).

Workloads Archive [8]. We use the first 1000 jobs of this trace as the input workload for the experiments which is long enough to reflect the behavior of spot price for different SIs. We assume that one EC2 compute unit is equivalent of a CPU core with capacity of 1000 MIPS[2]. As such, the selected workload needs about two weeks ($\approx$ 400 hours) to complete on a single m1.small instance. For other instance types we consider the linear speedup with the computing capacity in terms of EC2 compute unit which are listed in Table I. For each experiment, the results are collected for 50 simulation rounds.

Moreover, we assume a very high user's bid for each simulation (for example on-demand price) where we do not have any *out-of-bid* event in the execution of the given workload. We use the model with three components ($k = 3$) for both spot price and the inter-price time to show the trade off-between accuracy and complexity. In our experiments, the results of the simulations are accurate with a confidence level of 95%.

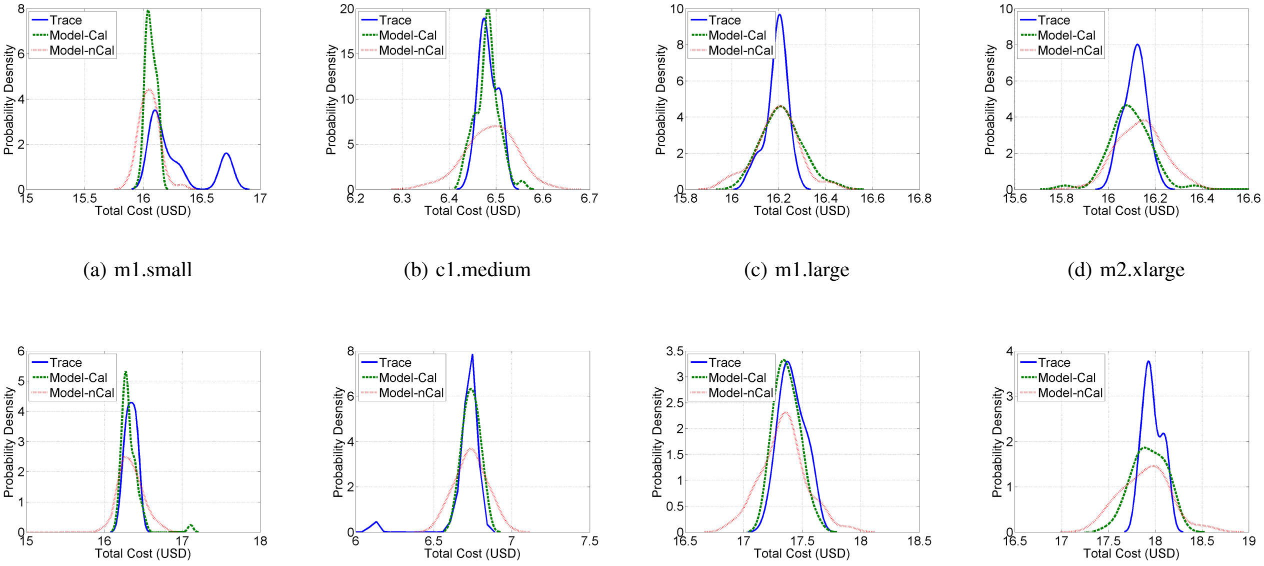
B. Results and Discussions

In the following, we present the results of two different set of experiments. First, we discuss the results of model validation where we have the price history that was included in the modeling process (i.e. Feb-2010 to Nov-2010). Second, we report the results from model validation using a new price history which was not included in the modeling process. The new price history is from December 2010 till mid-February 2011.

Figure 8 shows the model validation results where the probability density functions of the total monetary cost to run the given workload have been plotted for all types of SIs. In each plot, Trace, Model-Cal, and Model-nCal refer to the result of using the real price history, the model after calibration and the model before calibration, respectively. Based on these Figures, the proposed models match the real trace simulations with a high degree of accuracy, specially for the calibrated models. As we can see in these plots, in all cases the calibrated models are the better match with the trace simulations. As we expect, there are discrepancies in the model and trace simulation results for m1.small instance. However, the mean total cost for running the given workload for all SIs is very accurate where the maximum relative error is less than 3% for both calibrated and non-calibrated model, respectively.

Additionally, we report the model validation results where we use the new price history from December 2010 to mid-February 2011 to see the quality of the models for the future traces. The result of the simulations for the new price history are plotted in Figure 9. The results reveal that our models with three components still conform to the trace simulation results, except for m1.small instance. As mentioned earlier, spot price for m1.small instance is hard to fit and this is the reason of this inaccuracy. This means that for m1.small, we should use the model with more components (e.g. $k = 4$) to get the better accuracy. The calibrated models again match better with the trace simulations in comparison to the non-calibrated models for all SIs. Besides, the maximum relative error of the mean total cost for all SIs is less than 4% for both calibrated and non-calibrated model. Therefore, the proposed models are accurate enough for the new price history as well.

[2] Amazon mentioned that one EC2 compute unit has equivalent CPU capacity of a 1.0-1.2 GHZ 2007 Opteron or 2007 Xeon processor [3].



(a) m1.small (b) c1.medium (c) m1.large (d) m2.xlarge

(e) m1.xlarge (f) c1.xlarge (g) m2.2xlarge (h) m2.4xlarge

Fig. 9. Model validation for all SIs in eu-west for the new traces (Dec-2010 to mid-Feb-2011).

IX. Conclusions

We considered the problem of discovering models for Spot Instances in Amazon's EC2 data centers for spot price and the inter-price time. The main motivation behind this is to explore characterization of SIs that is essential in the design of stochastic scheduling algorithms and fault tolerant mechanisms (e.g. checkpointing and replication algorithms) in Cloud environments for spot market. We studied the price patterns of the Amazon's data centers for a one year period and provided a global statistical analysis to get a better understanding of these patterns. Based on this understanding and observed bimodality in probability densities, we proposed a model with mixture of Gaussians distribution with 3 or 4 components for eight different types of SIs. The proposed model is validated through simulations, which reveals that our model predicts the total price of running jobs on spot instances with a good degree of accuracy. We believe that the proposed model are helpful for researchers and users of spot Instances in Amazon's EC2 data centers as well as other IaaS Cloud providers that look forward to offer such a service in the near future.

In future work, we intend to consider the user's bid as another parameter and investigate how it can affect the distribution of failures. Moreover, we would like to design a brokering solution to utilize different types of Cloud resources to optimize the monetary cost as well as job completion time.

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