CHAPTER 6

STATISTICAL MODELING OF REAL WORLD CLOUD ENVIRONMENT FOR RELIABILITY AND ITS EFFECT ON ENERGY AND PERFORMANCE

6.1 INTRODUCTION

This chapter mainly focuses on how to handle the inherent unreliability of distributed systems. The reliability of the computing nodes in cloud, depends on them being alive. But instead of looking at them as a binary property as we have done in the previous chapters, we now find a new dimension of analysis in this chapter. A statistical property for reliability gave us a new dimension in a real world scenario. For this work, we have introduced performance measures suitable for reliability view. The real world scenarios have been simulated from real time traces to make the simulation viable. For repeatability we have used real time traces for our simulation. Jobs reach in a random fashion, the inter arrival time is exponentially distributed with average $1/\lambda_i$. The jobs are assumed to require service time exponentially distributed mean $1/\mu_i$. Job size includes program and data size under normal distributed nature with a given mean and variance. The jobs here are the Cloudlets in VM which resides in hosts as per the application. The Cloudlets (or) jobs arrive to VM residing temporarily to hosts and processing continues until processing elements are alive in a data center. The workload information of the VM is necessary to consolidate the host oversubscription and under-used servers in the data center. The Cloud resources are geographically
distributed and our scheduler acts as the medium between the Cloud users and the providers. Based on the availability of resources the scheduler occurs on the submissions of jobs and to maintain equilibrium to satisfy the SLA (Subrata et al 2008). Data center updates the information of its resources and they are hard estimate runtime of parallel applications where execution time is inversely proportional to CPU operating frequency (Garget et al 2009). These character ratings are learnt over-time based on the results returned by the provider to the server. All providers report their results to a centralized server, so a local character based reputation system can be employed.

**Table 6.1 Statistical Distribution to model reliability in Cloud Data Center (Sonnek et al 2007)**

<table>
<thead>
<tr>
<th>Field Density</th>
<th>Distribution (0,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular Cloud traffic</td>
<td>Uniform</td>
</tr>
<tr>
<td>Majority of reliable hosts; a few unreliable hosts</td>
<td>1-Pareto(a=1, b=0.1)</td>
</tr>
<tr>
<td>Majority of workers unreliable; major outage/failure of hosts</td>
<td>Pareto(a=1, b=0.2)</td>
</tr>
<tr>
<td>Reliable Environment; most hosts reliable</td>
<td>Normal: $\mu=0.9$, $\sigma=0.05$</td>
</tr>
<tr>
<td>50% reliable hosts; 50% unreliable</td>
<td>Bi-Normal: $\mu=0.2/0.8$, $\sigma=0.1$</td>
</tr>
<tr>
<td>Hostile Environment, eg., military scenarios</td>
<td>Normal: $\mu=0.3$, $\sigma=0.1$</td>
</tr>
</tbody>
</table>

The statistical real world scenario were taken to analyze the Cloud Host distribution based on reliability is as shown in Table 6.1. Reliability here has been taken as a statistical property instead of binary property where binary property is based on the hosts’ alive state. We estimate a provider’s repute $R$ at a time $t$ as shown in Equation (6.1).

$$R = \frac{t+1}{4+2}$$ (6.1)
where $\hat{t}$ and $\hat{q}$ are respectively the number of true results generated and the actual number of tasks attempted by the provider by time $t$. Instead of no knowledge of the actual repute rating, this expression actually helps in knowing the repute rating of a provider to $\frac{1}{2}$. The rating of each data center probability is updated each time and is assigned a job, based on the result. If the majority of answers in different statistical reliability scenario are the same then they are taken into consideration. For updating at every point in time these repute distribution are analyzed for each of the heuristics, we have analyzed both the accuracy relative to an optimal heuristic and the impact on system performance (Issarny et al 2011). Intuitively, this heuristic is based on the assumption that the probability of two providers returning the same wrong result independently is negligible, thus treating any matching answers to be pseudo-correct. The distribution is coupled to the minimum and maximum available hosts grouping by the repute. The repute defines the character of the Cloud delicately and gives better perception on allocation of VM to the hosts and the processing thereafter. To have the best Energy aware statistical model we define the performance and power consumption as two objectives since they are the major trade-off. To simulate this Multi-objective Optimization (MO) problem we have tabulated the repute based on statistical distribution and find the various factors involved in a hosts status in the data center.

6.2 DEFINITION AND ASSUMPTION

To analyze the cloud character we define the analytical parameters to be considered and these analytical parameters intend to solve the QoS perspective by giving an awareness of what trust a customer can expect. The definition and assumption for these analyzes is as follows

**Definition 1:** Job: An application $i$ in the form of a tuple which is heterogeneous in a Cloud environment and may be application domain
dependent. Independent users submit requests for provisioning of heterogeneous \( \nu \) VMs characterized by requirements to processing power defined in MIPS, amount of RAM and network bandwidth, the combination of mixed workload from different users lead to mixed workload and can be of various types of applications, such as HPC and web-applications, which utilize the resources simultaneously.

**Definition 2:** Data center Host Space: The data center host space is the set of the available host lists where VM is free based on our model to provision the jobs.

**Definition 3:** Repute: The reputation based Cloud character where a provider returns the exact possibility of dependence of a host.

**Definition 4:** Alive Host Group: The nodes which can handle the jobs at some time.

**Definition 5:** Possibility of Coalesce (POC): The POC is based on the maximum possible probability of the required coalesce between available under-loaded hosts and the prescribed VMs.

We simulate the Reliability based scheduling as described in Table 6.1, for handling the VM \( \nu \) in a host for the efficient processing of the incoming jobs and to avoid underutilization and also avoid oversubscription of the VMs. In addition, we also find the best Cloud environment for the job to acquire its share of processing space and the Coalesced data center which is to attain the objectives.

**Strike \( (\eta) \):** The Strike during an allocation is the number of Host in a data center Host Space for which many VMs are processed successfully providing a better repute in an Alive host group.
\[ \eta = host_{VMs} \]  

where \( host_{VMs} \) is the set of VMs successfully completed during that allocation.

**Hostware (\( \zeta \))**: The hostware is the mean number of Hosts in a data center Host space assigned to each VM during allocation in an Alive host group.

\[ \zeta = \frac{\sum_{v=1}^{j} j}{v} \]  

where \( j \) is the total number of hosts available during an allocation as shown in Equation (6.3).

When there is no available host then from Equation (6.3) we conclude that the Hostware is not active or no available active hosts due to variable dimensions on a status of hosts in a data center.

**Spare (\( \phi \))**: The Spare during an allocation is defined as the ratio of successfully completed VMs to the number of hosts available during the allocation, Considering the Alive host group as shown in Equation (6.4).

\[ \phi = \frac{\eta}{j} \]  

We simulated exhaustive simulations of the Statistical distribution we have considered and accordingly: the Cloud Server Character distributions described in Table 6.1, we take the host as N heterogeneous physical nodes, maximum available hosts \( Max_{hosts}^{\phi} \) which is the least individual number of under-loaded host in the host list and minimum available hosts \( Min_{hosts}^{\phi} \) which is the least individual number of over-loaded hosts in the hosts list. For each parameter setting, we compare our algorithms. For a given distribution and \( Max_{hosts}^{\phi} \), we set a best possible value equal to the spare \( \phi \). The \( P_{FREE} \)
processor is analyzed based on the real time Cloud scenario and simulated to find how efficient our algorithms intend to prove. The POC determine coalesce between the host character and workload information of cloudlet in a VM. This ensures that the spare of the various algorithms will be approximately the same, facilitating a comparison between our proposed algorithms and the traditional maximum density algorithm (Ishakian&Bestavros 2012). From the previous section, Definition and Assumptions we configure the algorithms and the parameters for analysis are considered. The VM selection algorithms defined earlier like the proposed MPP, MMT are used and they form groups for each VM migratable list of the cloud statistical reliability distribution and the corresponding values are plotted in graphs and discussed in Section 6.3. Many rounds of experiments have been constructed and the scheduling algorithms and the objectives have been graphed.

The possibility of coalesce is the probability of finding the minimum CPU utilization or the Host workload to which coalesce has to be maintained to the Minimum Energy Heuristics and the Cloud Character when the threshold variance of CPU utilization by our algorithm exceeds. The Energy toll by the start of SLA violation has to be effectively managed by the VM migration. The CPU utilization is directly proportional to the energy consumed or the Host workload which in-turn is responsible to handle the VMs. The Energy consumed by the underutilized servers has to be maintained in coalesce with the overused servers. One can imagine scenarios in which either metric throughput (or) success rate would be preferred over the other. Thus, neither throughput nor success rate alone is a sufficient metric for determining an optimal value of target. In particular, if we wish to bind the latency experienced by individual tasks, success rate is a more important metric than throughput as a high success rate reduces the performance
degradation and improves the QoS. To analyze high success rate the product of energy and performance degradation has been performed.

We use the proposed algorithms to form groups by randomly adding hosts until coalesce is met. We compute the POC and create pairs to achieve coalesce between the best Cloud character and the best energy heuristics. We handle this parameter to leverage the energy consumed in a data center where VMs are acquired in a host by the CPU. The host overloading has to be minimized by maintaining the VM migration to be processed at a host which is not overloaded. We have also designed a Cloud Character which is based on the repeatability aspect of mixture of the Cloud mixed workload. The objective has been to find a Possibility of Coalesce between the Energy and Workload statistical Cloud model to destine a CQR and Min energy aware host. The algorithms are used to find the relationship of cloud reliability model and find an efficient scenario where cloud works best. The real world cloud reliability distributions were simulated for different algorithms such as LR MMT, LR MPP and CQR MPP. We discuss the results that we obtained by introducing the proposed algorithms to the real world scenarios.

6.3 RESULTS AND DISCUSSION

We have simulated the actual cloud model the best possible QoS bearing the trade-off involving the performance as well as power ingestion. The proposed model efficiently harnesses energy as density of the VM increases but the energy for the traditional data centers proves better for lower density of VM approximately less than 400. The VM migration lessens by more than 76% for the proposed model and thus reduces SLAV. CQR MPP energy increases linearly by 10% as the density Virtual Machine Migration increases as the number of VM for a day simulated in an algorithm. The time
of completion of the VM migration helps in the reduction of SLAV and helps in the QoS that can be delivered. The Energy fluctuates due to the resource availability and the performance harnessing helps in better tackling this issue. As the Energy consumed decreases from 100 kWh, the VM migration reduces for our proposed model exponentially by 5% for a 1052 VMs used for simulation.

![Figure 6.1 Energy spent for the Cloud Reliability Distribution](image)

**Figure 6.1 Energy spent for the Cloud Reliability Distribution**

In Figure 6.1 the analysis of the Energy for NPA (Non Power aware) and DVFS (Dynamic Voltage Frequency Scaling) is done with respect to our proposed model which is drastically efficient when compared to NPA. For a uniform distribution the Energy for NPA is around 2400 kWh whereas CQRMPP is 120 kWh. Energy Consumption depends on the hosts in a data center and QoS to a customer can be satisfied only when a lesser SLAV occur which in turn depends on the Virtual Machine Migration takes a lesser time and with a lesser frequency of occurrence. Energy when the Cloud character distribution is compared has a drastic improvement with the proposed CQR where localized subsets are analyzed and the algorithms are simulated, CQRMPP which combines the CQR and minimum energy heuristics and thus enables the best energy as in Figure 6.1 saving of up to 2000 kWh compared
to NPA and 40% to 50% lesser energy compared to DVFS. Thus energy is better for proposed system and efficient when compared to the traditional systems. We perform multi-objective optimization and forms coalesce between the consumer and the provider to handle the trade-off between problem of energy and performance efficient dynamic consolidation of VMs performance always hinders the energy perspective.

For our simulation experiments as shown in the Figure 6.2, the mean strike across multiple simulations conducted is around 40% to 60% and CQR MPP method improves the strike. The LR MMT has a better strike in all real world scenarios except for uniform and 1-Pareto distribution. The LR MPP is outperformed by 10 to 20% by the CQR MPP and LR MMT. The Strike and spare for various real time scenario of the Cloud Character model helps to study the available VMs which can be allocated to a host with a larger probability of reliability. The spare has a substantial improvement for CQR MPP compared to both LR MPP and LR MMT, the average efficiency for spare of CQR MPP has been to the amount of 28% compared to LR MPP, our proposed algorithm.

![Figure 6.2 Strike and Spare for the Cloud reliability Distribution analysing three different algorithms for repute](image)
Figure 6.3  Performance Degradation and Energy Consumption for the Cloud reliability Distribution analysing three different algorithms for repute

We analyze the algorithms and try to improve the strike and spare of coalesce between the processes and processing element. The host status varies at a point in time and has to be harnessed to attain better reliability. There can be several unreliable coalesce from the available (or) assumed high reliability character based distribution that we exhibit. Energy consumption in Figure 6.3 is lesser to a major extent when CQR MPP is in play due to the uniqueness of the prediction and the proposed MPP strategy.

The characteristics of the servers and data on their power consumption are considered (Corporation 2012). The metrics we consider is the Performance degradation and the Energy consumption by physical nodes. The reduction of performance degradation due to migration is possible as energy consumption increases. Our proposed model has proved better when energy consumption decreases the performance degradation due to migration is comparatively reduced when a traditional algorithm is being executed. The VM uses lesser workload as specified in PlanetLab workload data, the consolidation of VM is hence necessary and devising algorithm for this consolidation has been simulated by our model. Our model is efficient in the trade-off point of view with respect to performance and power consumption.
We have simulated the cloud model the best possible reliability bearing the trade-off between the performance and power consumption. The Effect of the VM size with respect to the SLA time per active host and Energy has been analyzed for a day at the PlanetLab in Table 6.2. All the results shown are compared to legacy algorithms in CloudSim, related parameters are exhaustively compared to our CQRMP algorithm. The scarcity of the resources increases the energy consumption as we discussed earlier, number of Host Shutdown depends on the Energy consumption.

Table 6.2  Energy spent and the SLATAH on 800 heterogeneous nodes in a 24 hour simulation

<table>
<thead>
<tr>
<th>No. of VMs</th>
<th>LR MMT Energy</th>
<th>CQRMP Energy</th>
<th>LR MMT SLATAH</th>
<th>CQRMP SLATAH</th>
</tr>
</thead>
<tbody>
<tr>
<td>1052</td>
<td>116.71</td>
<td>105.80</td>
<td>19.54%</td>
<td>4.03%</td>
</tr>
<tr>
<td>1042</td>
<td>115.96</td>
<td>104.66</td>
<td>17.74%</td>
<td>4.16%</td>
</tr>
<tr>
<td>1022</td>
<td>109.12</td>
<td>98.10</td>
<td>17.99%</td>
<td>3.88%</td>
</tr>
<tr>
<td>920</td>
<td>100.39</td>
<td>89.87</td>
<td>16.13%</td>
<td>3.68%</td>
</tr>
<tr>
<td>820</td>
<td>80.78</td>
<td>71.28</td>
<td>15.65%</td>
<td>3.65%</td>
</tr>
<tr>
<td>720</td>
<td>61.46</td>
<td>54.25</td>
<td>15.18%</td>
<td>3.25%</td>
</tr>
<tr>
<td>520</td>
<td>41.62</td>
<td>36.94</td>
<td>11.88%</td>
<td>2.77%</td>
</tr>
<tr>
<td>220</td>
<td>27.44</td>
<td>24.57</td>
<td>8.58%</td>
<td>2.44%</td>
</tr>
</tbody>
</table>

The SLA performance degradation due to migration for the traditional algorithms is almost zero percentage and as consolidation is done the proposed algorithm harness the resources, increasing the SLATAH but in turn reduces Energy consumption. Energy levels are exponentially 10% lesser throughout the simulation and CQRMP SLA performance degradation due to migration is almost linear at 0.06% throughout the simulation considered. As the density of VMs increase and Energy consumption increases the CQRMP SLATAH increases by about 0.05% as in Figure 6.4. The density
of VMs when increased shows linear dependence of the number of Host Shutdown when there is an exponential increase. The Energy consumed is proportional and denotes parallel curves as Host Shutdown shown in Figure 6.4. The SLATAH and PDM vary as Energy of a simulation having 1052 VMs and 800 heterogeneous nodes the lesser the Energy consumption higher is the SLAV and this is reflected in SLATAH. The energy spent and the CQRMPP SLATAH of the proposed system proved efficient since in LRMMT the SLATAH is higher this enabled the energy to be decreased due to better VM consolidation.

![Graph showing comparison between CQRMPP and LRMMT for host shutdown](image)

**Figure 6.4 Analysis of Number of Host shutdown for proposed and legacy methods on 800 heterogeneous nodes in a 24 hour simulation**

The mean value of the sample means of the time before a host is switched to the sleep mode for the CQR-MPP algorithm combination is 864 seconds with the 95% CI: (820, 908). Performance Degradation is higher since there is more utilization of resources under constraints unlike the hosts being overused and more servers left underused or not used at all. This means that on an average a host is switched to the sleep mode after approximately 14.4 minutes of activity. The mean number of host transitions to the sleep
mode for our experiment setup (the total number of hosts is 800) per day is 771 with 95% CI: (707, 835). The mean value of the sample means of the time before a VM is migrated from a host for the same algorithm combination is 20.26 seconds with the 95% CI: (19.9, 20.62). The mean value of the sample means of the execution time of the CQR-MPP algorithm on a server with an Intel Core i7 (2.40 GHz) processor and 2 GB of RAM is 0.10 ms with the 95% CI: (0.09, 0.11). The SLATAH and PDM vary as Energy of a simulation having 1052 VMs and 800 heterogeneous nodes the lesser the Energy consumption, higher is the SLAV and this is reflected in SLATAH. Consolidation of the hosts in turn increases the Host Shutdown increasing the Energy requirement of the available hosts and Migration Time lessens which increases SLAV. Consolidation of the hosts in turn increases the Host Shutdown increasing the Energy requirement of the available hosts and Migration Time lessens which increases SLAV. Thus our proposed algorithms CQRMP proves to be energy efficient than the legacy algorithms to about 36%.

6.4 SUMMARY

We have deployed the Cloud energy efficient strategies by performing dynamic consolidation and used statistical models to harness the trust that is required for a consumer on Cloud. Thus the trade-off has been harnessed by our proposed model and simulated. The SLA and QoS metrics lead to the trade-off between problem of energy and performance efficient dynamic consolidation of VMs. The results have proved to be better than the available traditional methods in the Energy perspective in the present Cloud infrastructure and maintaining the server utilization to a better level and in avoiding fluctuation of servers or hosts thereby reducing the running expenditure of the over-provisioned servers. Performance efficient dynamic consolidation of VM has helped to reduce the energy consumption to about
36% and our model proved efficient and since there has been an increase in performance degradation which helped to maintain a lower SLAV. The proposed algorithms prove better and have harnessed the energy consumption although higher energy consumption maintained a lower SLAV thereby decreasing the carbon footprint in the present IT infrastructure. In the next chapter we consolidate our inference and the future thoughts.