**Abstract**

**Background/Objective:** Dynamic VM consolidation has been known as one from several ways to reduce energy consumption in cloud data center. The problem in reducing energy consumption with dynamic VM consolidation has recognize as NP-Hard problem that divided into four subs, where VM selection is one of sub-problem. The objective VM selection is to choose the best VM that suitable to move from overload host and avoid oversubscription host. **Methods:** This research proposed novel VM selection model based on Fuzzy Logic, Markov Normal Algorithm (MA) and Existing VM Selection (FuMAEVMS) in dynamic VM consolidation. Moreover, RAM VM and max MIPS VM are consider as attribute to be used. The proposed VM selection model have been evaluated using Cloudsim with datasets from PlanetLabs in various condition of VM instance. The research measured the performance using several parameters such as Energy Consumption (EC), SLA Violation (SLAV), SLA Time per active host (SLATAH) and Performance Degradation Due Migration (PDM). FuMAEVMS were compared with existing VM selection such as constant first selection (CFS), minimum migration time (MMT), random choice (RC) and maximum correlation (MC). **Findings:** FuMAEVMS as Novel VM selection capable to decide which VM that should be migrate from overload host in various condition VM instances that gives improvement of energy efficiency in cloud data center. We analyze the used of fuzzy logic in categorizing attribute VM capable to help in minimize rules production in Markov Normal Algorithm. This condition gives benefit to MA in deciding suitable existing VM selection such as CFS, MMT or MC to be used in migrating VM. **Improvement:** Results experiment has showed FuMAEVMS VM selection capable to reduced energy consumption in cloud data center significantly up to 4.45% when applied in dynamic VM consolidation compared with RC, MMT and MC.

**Keywords:** CFS, Cloud Data Center, Energy Efficiency, Fuzzy, MC, Markov Normal Algorithm, MMT

1. **Introduction**

Cloud computing provide ease of use computation depends on users requirement. Flexibility of this concepts was deployed in virtual machine (VM) instances that run under physical machine. The flexibility that offers by cloud computing services gives tradeoff that caused massive electric energy consumption in cloud data center and expected will growth.

Virtual technology capable to make efficiency in providing amount of physical hardware in cloud data center. However, virtual machine can lead to performance degradation and high electricity consumption, if not managed. Moreover the idle condition of server still consume almost 50% energy from its peak power. Therefore, cloud data center needs to employ a strategy to reallocate physical resources dynamically to maximizing preserver utilization for optimizing energy efficiency. Distributed dynamic VM consolidation is effective strategy to solve those problem.

The problem in allocating VM to optimize energy consumption in cloud data center dynamically has consider as NP-Hard problem. The problem in dynamic VM consolidation in allocating virtual machine has divided into several parts. VM selection is one of sub-problem that responsible in deciding which VMs should be migrated away from overloaded hosts and to avoid oversubscription.
host. VM selection that effective to choose suitable VM to migrate that capable improve energy efficiency in cloud data center are very important. Thus, many researcher have try to take a part in solving this problem \cite{6,13}.

Fuzzy logic has been introduced by Lotfi Zadeh in 1965\cite{12}. The capability of Fuzzy logic that able to blur crisp number with basic knowledge from expert has given flexibility in clustering object\cite{15}. In several works, fuzzy techniques has adopted in scheduling and resources allocation problems\cite{16,21}. However, only few works that applied fuzzy logic in dynamic VM consolidation specially to solve VM selection. Masoumouzadeh, et al.\cite{8}, has proposed Fuzzy Q-learning for VM selection in dynamic VM consolidation, however the research only considering CPU utilization as attribute VM and have not tested the performance of the model in various VM instances. In the previous work\cite{14}, various instance VM with homogeneous or heterogeneous condition could influences the performance of VM selection in dynamic VM consolidation.

Markov Normal Algorithm or known as semi-thue system is computational model that have same capability with Turing machine\cite{24,25,27}. Several works have try to adopt the model in solving many cases such as in math, image and signal processing or language parser\cite{24,26,27,28}. However, this model have received little attention and never been tried to solved problems in cloud research area especially in dynamic VM consolidation.

Based on the information above, this research has been motivated to solve VM selection problems in dynamic VM consolidation for improving energy efficiency. We proposed VM selection FuMAEVM, which combine Fuzzy logic with computation model Markov Normal Algorithm and existing VM selection such as CFS, MMT and MC. Moreover, we only used two attributes in migrating VM there are RAM VM and max MIPS CPU VM. The proposed model will be evaluated with real workload data and tested in various condition VM instances. The results of proposed VM selection were compared with other VM selection such as constant first selection CFS\cite{6}, minimum migration time MMT, random choice RC and maximum correlation MC\cite{7} energy efficient become an important issue around the world that leads to the green technology research in cloud computing area. This research focus in efficiently electrical energy consumption in Cloud Computing area especially by improving VM selection policy in dynamic VM consolidation. The procedure of overall strategy Dynamic VM consolidation consist with four basic phase (1. CPS) VM selection is part of Constant Position VM selection (CPS) our previous work\cite{6} energy efficient become an important issue around the world that leads to the green technology research in cloud computing area. The research focus in efficiently electrical energy consumption in Cloud Computing area especially by improving VM selection policy in dynamic VM consolidation. The procedure of overall strategy Dynamic VM consolidation consist with four basic phase (1. CFS works by selecting first index VM in specific overload host as seen in equation (1).\n
\[
v = (first, V_j), \text{where } first = \left(1, |V_j|\right)
\]  

(1)

The lists of VMs $V_j$ in overloaded host $j$ that have “first” index will be select to migrate and denoted as $v$, where the first position here is gathered by selecting the first VM that have index “1” from the overall size VMs $|V_j|$.\n
### 2.2 Random Choice\n
In Random Choice\cite{8}, selecting VM in overload host with random index based on uniformly distribution. Where VMs $V_j$ is allocated to a host $j$, as shown in formula (2).\n
\[
v \equiv U(0, |V_j|)
\]  

(2)

### 2.3 Minimum Migration Time\n
In minimum migration time MMT VM selection\cite{6}, it migrates a VM $v$ that requires the minimum time to complete a migration relatively to the other VMs allocated to the host as shown in equation (3), where the migration time was estimated as the amount of utilization RAM VM divided by available spare network bandwidth for the host $j$. $V_j$ are set of VMs currently allocated to the host
The MMT will finds a VM \( v \). Where \( \text{RAM}(\alpha) \) is the amount of \( \text{RAM} \) currently utilized by the VM \( \alpha \); and \( \text{NET} \) is available spare network bandwidth for the host \( j \).

\[
\forall v \in V_j \mid \forall \alpha \in V_j, \left( \frac{\text{RAM}(\alpha)}{\text{NET}(j)} \leq \frac{\text{RAM}(\alpha)}{\text{NET}(j)} \right)
\]

### 3. Proposed FuMAEVMS

FuMAEVMS is VM selection model that select suitable VM in specific overloaded host. In dynamic VM consolidation, selection of virtual machine is necessary when host overload mechanism in cloud data center decided specific host was detected as overload.

The concept of proposed VM selection model, applied Fuzzy logic for categorizing attribute of VM in host that detected overload by Host Overload Detection. Moreover, Markov Normal Algorithm MA applied to decide which existing VM selection techniques such CFS, MMT and MC that suitable to select VM in its overloaded host. Overall steps of proposed VM Selection model FuMAEVMS are showed in equation (8-20).

\[
v(\text{outputMA}) = \begin{cases} \text{CFS} & \text{outputMA} = \text{cfs} \\ \text{MMT} & \text{outputMA} = \text{mmt} \\ \text{MC} & \text{outputMA} = \text{mc} \end{cases}
\]

In formula (8), \( v \) is selected VM that will be migrate from overloaded host. Where CFS is VM selection method that calculate in formula (1), MMT calculate in formula (3) and MC calculate in formula (4-7).

\[
\text{outputMA} = \{\text{cfs}, \text{mmt}, \text{rc}, \text{mc}\}
\]

### 2.4 Maximum Correlation

In Maximum Correlation VM Selection, it select the VMs that have higher probability correlation between resources usage by application that running on oversubscribed server. To estimate the correlation between CPU utilization by VM it used multiple coefficient correlation. The steps of VM selection is start from augmented matrix to observed independent variables and vector observation, as shown at (4).

\[
X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,n-1} \\ \vdots & \ddots & \vdots \\ x_{n-1,1} & \cdots & x_{n-1,n-1} \end{bmatrix}, \quad Y = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}
\]

Where \( X_1, X_2, \ldots, X_n \) be random variable that \( n \) represent CPU utilization of allocation VMs in a host. \( y \) is represent as VM that currently consider to migrate. \( n - 1 \) is random variable independent and \( 1 \) variable \( y \) is dependent, then calculate vector predicate value of dependent random variable denote by \( \hat{y} \) (5):

\[
\hat{y} = Xb, \text{where } b = \left( X^T X \right)^{-1} X^T y
\]

After vector predicate is found, then calculate multiple correlation coefficient by (6):

\[
R^2_{\hat{y} | x_1,\ldots,x_{n-1}} = \frac{\sum_{i=1}^{n-1} (y_i - [m_y]) \sum_{i=1}^{n-1} (\hat{y}_i - [m_{\hat{y}}])^2}{\sum_{i=1}^{n-1} (y_i - [m_y])^2 \sum_{i=1}^{n-1} (\hat{y}_i - [m_{\hat{y}}])^2}
\]

\[
(6)
\]

Where \( m_y \) and \( m_{\hat{y}} \) are the sample means of \( y \) and \( \hat{y} \) respectively. Multiple correlation coefficient for each \( Xi \) denoted as \( R^2_{x_1,\ldots,x_{n-1}, x_{i+1},\ldots,x_n} \). The maximum correlation policy finds a VMs \( v \) is denote as (7)

\[
v \in V_j \mid \forall a \in V_j, \left( R^2_{x_1,\ldots,x_{i-1}, x_{i+1},\ldots,x_n} \right) \geq \left( R^2_{x_1,\ldots,x_{i-1}, x_{i+1},\ldots,x_n} \right)
\]
The implication rules of Markov normal algorithm $\Pi$ in equation (13) is used to give decision of which existing VM selection technique that will be used for migrating VM in specific overloaded host. Where $N$ is natural number, with $\alpha \in N$, $\alpha = \{1,2, ..., m\}$, $m$ is max index of category attribute "Ram VM", and $\beta \in N$, $\beta = \{1,2, ..., n\}$, $n$ is max index of category attribute "Mips VM". The insides of production rules $\Pi$, are consists with number of sequence Production rules $P_{\psi_1}, P_{\psi_2}, P_{\psi_3}, P_{\psi_4}, \ldots, P_{\psi_{15}}$.

Where, $\psi_1 = \{1,2, ..., m \times n\}$, $\psi_2 = \{\psi_1 + 1, ..., \psi_1 + m \times n\}$, $\psi_3 = \{\psi_2 + 1, ..., \psi_2 + m \times n\}$, $\psi_4 = \{\psi_3 + 1, ..., \psi_3 + m \times n\}$, $\psi_5 = \{\psi_4 + 1, ..., \psi_4 + m \times n\}$, $\psi_6 = \{\psi_5 + 1, ..., \psi_5 + m\}$, $\psi_7 = \{\psi_6 + 1, ..., \psi_6 + m\}$, $\psi_8 = \{\psi_7 + 1, ..., \psi_7 + m\}$, $\psi_9 = \psi_8 + 1$, $\psi_{10} = \psi_9 + 1$, $\psi_{11} = \psi_{10} + 1$, $\psi_{12} = \psi_{11} + 1$, $\psi_{13} = \psi_{12} + 1$, $\psi_{14} = \psi_{13} + 1$

$\sum_{\psi_1} = \{\text{String}_{MA}\}$

$\Gamma = \{N, \text{Ram}, \text{Mips}, \text{mc}, \text{mmt}, \text{cfs}, \#, \varepsilon\}$

$P_0 = \{P_{\psi_{15}}\}$

$\Pi = \{P_{\psi_1}, P_{\psi_2}, P_{\psi_3}, P_{\psi_4}, \ldots, P_{\psi_{15}}\}$

$\{V1\text{Ram}_1\text{Mips}_2\#V2\text{Ram}_3\text{Mips}_1\#\ldots\text{String}_{Vj\#}\}$ It is representing value of each VM and its attribute that will be migrated in overloaded host. Value of each attribute VM, has been categorized using fuzzy logic in equation (18–20).

$\text{String}_{MA} = \{\text{String}_{Vj\#}\}$

where, $\text{String}_{Vj\#} = \{A_{(j,k,l)}(D(j,k,l))\}$

$A_{j,k,l}$ is attribute VM with $j$ is overloaded host, $k$ is index VM, and $l$ is index of attributes VM. In this proposed model VM selection, we only consider two attribute VM $A_{j,k,1}$ is Ram VM , and $A_{j,k,2}$ is max MIPS VM. $D(j,k,l)$ is value of attribute $A_{j,k,1}$ that represent as categorical value, which is gathered from higher degree of membership fuzzy as seen in formula (17).

$(D(j,k,l), \text{val}) = \max(\mu_{(j,k,1)}, \mu_{(j,k,2)}, \mu_{(j,k,3)})$

(17)

The membership function in fuzzy logic, which is representing category of each attribute in $\mu_{(j,k,1)}$, $\mu_{(j,k,2)}$, $\mu_{(j,k,3)}$ are gathered from equation (18–20). Where attribute $l$ in VM with index $k$ from overload host $j$ will be classify using membership triangular ($T - \text{function}$). Notation $\text{att}(j,k,l)$ is numerical value of specific VM in overloaded host, where $\text{max}_\text{att}(l)$ is maximum value of attribute $l$ in cloud data center.
4. Evaluation

4.1 Dynamic VM Consolidation

Even the concern in this research is only VM selection area, dynamic VM consolidation should works together with other parts. The other parts that required are host overload detection, host underload detection, and VM placement. In overload detection we used local regression technique LR, in underload detection we used trivial technique that moves all VM in underload host, and in VM placement we used power aware best fit decreasing PABFD based on research Beloglazov.

4.2 Workload Data

Workloads datasets are very important in evaluation process. To make a simulation-based evaluation applicable in real world, it required real workload data. We used the workload trace data from PlanetLab that consist with CPU utilization of thousand VMs from many servers in 500 places around the world.

4.3 VM Instance

There are four conditions VM Instance would be evaluated, following the previous work. First condition is Random VM Instances that generates workload traces in heterogeneous VM Instance characteristic such as, High CPU (2500 MIPS, 0.87 GB), Medium CPU (2000 MIPS, 1.7 GB) Small CPU (1250 MIPS, 1.7 GB) and Micro CPU (500 MIPS, 613 MB).

The second condition is High VM Instance that only generates workload in homogenous VM Instance with characteristic (2500 MIPS, 0.87GB). The third and four condition are Small and Micro VM Instances. Each condition also generates workload in homogenous VM Instance with characteristic (1250 MIPS, 1.7GB) and (500 MIPS, 613MB).

4.4 Performance Measurements

The performance measurements in this research consist with Energy Consumption (EC), SLA Violation Time per Active Host (SLATAH), Performance Degradation Measurements (PDM) and SLA Violation (SLAV).

4.5 Tools

This research used CloudSim toolkit to simulate the performance of the proposed method. The simulation tools are setup as 800 physical host with series HP ProLiant ML 110 G5 (Intel Xeon 3075, 2 cores × 2660 MHz, 4 GB). The server has frequency rating 2660 MIPS each core and 1GB/s network bandwidth. Detail power consumption characteristic of the server could be showed in Table 1.

5. Result and Discussion

Detail of result experiment in this paper could be seen in Table 2–5, where various condition of VM instances have given influence to all VM selection model in performing energy consumption and quality of services in cloud data center. The implementation of Fuzzy Logic as part of proposed VM selection for categorizing attribute in each VM, was able to classify the types of attributes VMs such as Ram and Mips into several categories. The impact of categorizing attributes VMs in this process have given benefits to Markov Normal Algorithm in building decision rules. Because of that, the implication rules in MA could be generates very simple to choose proper existing VM selection technique such as CFS, MMT or MC with difference condition of instance VM.

As results in Figure 1, our proposed VM selection model capable to optimizing the energy efficiency consumption in cloud data center around 2.07% up to 4.45%, compared with existing VM selection that has been proposed by Beloglazov such as RC, MMT and MC. The proposed model works significantly in all condition of VM instance and capable to reduce the average of energy consumption in cloud data center evaluated with all datasets as shown in Table 2. Although the performance of FuMAEVM has showed significant improvements in reducing energy consumption of cloud data center compared with RC, MMT and MC selection. In the other hands, the proposed model has closed energy efficiency performance, which is draw compared with CFS our existing works.

Moreover, in Table 3 has showed the performance SLA time per active host SLATAH of several VM selection in various condition of VM instances. FuMAEVM has perform better SLATAH compared with RC, MC

### Table 1. Power Consumption Characteristic

| Server       | 0%  | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 100% |
|--------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| ProLiant G5  | 93.7| 92.9| 97  | 110 | 116 | 121 | 125 | 129 | 133 | 135 |      |
| Workload | TypeVm Instance | LR FUMAEVMS | LR CFS | LR MMT | LR RC | LR MC |
|----------|----------------|-------------|-------|--------|-------|-------|
| 20110303 | Random          | 147.83      | 147.66| 164.18 | 153.00| 151.06|
|          | Mikro           | 64.63       | 64.85 | 64.85  | 66.63 | 64.63 |
|          | Small           | 128.48      | 128.48| 128.48 | 131.60| 131.13|
|          | High            | 235.41      | 235.41| 235.41 | 236.62| 237.55|
|          | Average         | **144.09**  |       |        |       |       |
| 20110306 | Random          | 112.68      | 112.68| 124.24 | 115.28| 114.45|
|          | Mikro           | 51.2        | 51.81 | 51.81  | 52.37 | 51.20 |
|          | Small           | 98.31       | 98.31 | 98.31  | 100.82| 100.96|
|          | High            | 176.5       | 176.50| 176.50 | 177.98| 178.19|
|          | Average         | **109.67**  |       |        |       |       |
| 20110309 | Random          | 126.93      | 126.40| 144.33 | 130.25| 131.33|
|          | Mikro           | 56.56       | 56.92 | 56.92  | 57.33 | 56.56 |
|          | Small           | 105.52      | 105.52| 105.52 | 108.27| 108.31|
|          | High            | 190.27      | 190.27| 190.27 | 191.34| 192.93|
|          | Average         | **119.82**  |       | **119.78** |       |       |
|          |                  | **126.36**  |       |        |       |       |
| 20110325 | Random          | 136.16      | 136.00| 154.01 | 140.14| 141.12|
|          | Mikro           | 58.98       | 58.98 | 58.98  | 61.53 | 58.98 |
|          | Small           | 112.06      | 112.06| 112.06 | 114.08| 112.49|
|          | High            | 198.41      | 198.41| 198.41 | 200.26| 200.00|
|          | Average         | **126.40**  |       |        |       |       |
| 20110403 | Random          | 200.42      | 200.61| 221.98 | 205.60| 206.22|
|          | Mikro           | 88.68       | 88.68 | 88.68  | 90.37 | 88.68 |
|          | Small           | 175.09      | 175.09| 175.09 | 177.64| 178.08|
|          | High            | 321.93      | 321.93| 321.93 | 324.61| 322.70|
|          | Average         | **196.53**  |       |        |       |       |
| 20110409 | Random          | 161.41      | 161.70| 181.81 | 165.32| 165.59|
|          | Mikro           | 73.6        | 73.60 | 73.60  | 75.71 | 73.60 |
|          | Small           | 139.18      | 139.18| 139.18 | 142.86| 142.36|
|          | High            | 253.55      | 253.55| 253.55 | 254.78| 254.75|
|          | Average         | **156.94**  |       |        |       |       |
| 20110411 | Random          | 157.41      | 157.89| 177.39 | 162.03| 164.36|
|          | Mikro           | 71.17       | 70.61 | 70.61  | 72.79 | 71.17 |
|          | Small           | 137.13      | 137.13| 137.13 | 137.79| 138.37|
|          | High            | 246.94      | 246.94| 246.94 | 248.66| 247.55|
|          | Average         | **153.16**  |       | **153.14** |       |       |
| 20110412 | Random          | 136.24      | 136.64| 153.49 | 140.96| 141.00|
|          | Mikro           | 61.34       | 60.65 | 60.65  | 62.91 | 61.34 |
|          | Small           | 117.26      | 117.26| 117.26 | 119.35| 120.31|
|          | High            | 212.81      | 212.81| 212.81 | 213.70| 213.23|
|          | Average         | **131.91**  |       | **131.84** |       |       |

Table 2. Energy Consumption in all variant VM instance (kWh)
| Workload | TypeVm Instance | LR FUMAEVMS | LR CFS | LR MMT | LR RC | LR MC |
|-----------|----------------|-------------|--------|--------|-------|-------|
| 20110303  | Random         | 6.72%       | 6.75%  | 5.82%  | 7.21% | 6.88% |
|           | Mikro          | 2.97%       | 3.01%  | 3.01%  | 3.09% | 2.97% |
|           | Small          | 8.31%       | 8.31%  | 8.31%  | 8.56% | 8.49% |
|           | High           | 4.79%       | 4.79%  | 4.79%  | 4.89% | 4.83% |
|           | Average        | 5.70%       | 5.72%  | 5.48%  | 5.94% | 5.79% |
| 20110306  | Random         | 6.63%       | 6.63%  | 5.95%  | 6.98% | 6.86% |
|           | Mikro          | 2.91%       | 3.02%  | 3.02%  | 3.03% | 2.91% |
|           | Small          | 8.12%       | 8.12%  | 8.12%  | 8.51% | 8.61% |
|           | High           | 4.84%       | 4.84%  | 4.84%  | 4.92% | 4.99% |
|           | Average        | 5.63%       | 5.65%  | 5.48%  | 5.86% | 5.84% |
| 20110309  | Random         | 7.39%       | 7.37%  | 6.56%  | 7.87% | 7.85% |
|           | Mikro          | 3.12%       | 3.14%  | 3.14%  | 3.10% | 3.12% |
|           | Small          | 8.74%       | 8.74%  | 8.74%  | 8.94% | 8.90% |
|           | High           | 5.54%       | 5.54%  | 5.54%  | 5.81% | 5.75% |
|           | Average        | 6.20%       | 6.20%  | 6.00%  | 6.43% | 6.41% |
| 20110325  | Random         | 7.04%       | 7.04%  | 6.06%  | 7.33% | 7.40% |
|           | Mikro          | 3.04%       | 3.04%  | 3.04%  | 3.10% | 3.04% |
|           | Small          | 8.41%       | 8.41%  | 8.41%  | 8.59% | 8.42% |
|           | High           | 5.04%       | 5.04%  | 5.04%  | 5.24% | 5.12% |
|           | Average        | 5.88%       | 5.88%  | 5.64%  | 6.07% | 6.00% |
| 20110403  | Random         | 6.98%       | 6.98%  | 5.99%  | 7.43% | 7.42% |
|           | Mikro          | 3.06%       | 3.06%  | 3.06%  | 3.11% | 3.06% |
|           | Small          | 8.45%       | 8.45%  | 8.45%  | 8.67% | 8.63% |
|           | High           | 5.00%       | 5.00%  | 5.00%  | 5.33% | 5.16% |
|           | Average        | 5.87%       | 5.87%  | 5.63%  | 6.14% | 6.07% |
| 20110409  | Random         | 7.09%       | 7.07%  | 6.05%  | 7.51% | 7.21% |
|           | Mikro          | 3.07%       | 3.07%  | 3.07%  | 3.15% | 3.07% |
|           | Small          | 8.52%       | 8.52%  | 8.52%  | 8.71% | 8.67% |
|           | High           | 5.24%       | 5.24%  | 5.24%  | 5.48% | 5.48% |
|           | Average        | 5.98%       | 5.98%  | 5.72%  | 6.21% | 6.11% |
| 20110411  | Random         | 7.18%       | 7.08%  | 6.24%  | 7.58% | 7.38% |
|           | Mikro          | 3.07%       | 3.06%  | 3.06%  | 3.13% | 3.07% |
|           | Small          | 8.58%       | 8.58%  | 8.58%  | 8.74% | 8.74% |
|           | High           | 5.24%       | 5.24%  | 5.24%  | 5.48% | 5.41% |
|           | Average        | 6.02%       | 5.99%  | 5.78%  | 6.23% | 6.15% |
| 20110412  | Random         | 7.07%       | 7.05%  | 6.20%  | 7.55% | 7.59% |
|           | Mikro          | 3.08%       | 3.08%  | 3.08%  | 3.12% | 3.08% |
|           | Small          | 8.63%       | 8.63%  | 8.63%  | 8.72% | 8.82% |
|           | High           | 5.61%       | 5.61%  | 5.61%  | 5.66% | 5.55% |
|           | Average        | 6.10%       | 6.09%  | 5.88%  | 6.26% | 6.26% |
| Workload  | Type Vm Instance | LR FuMAEVMS | LR CFS | LR MMT | LR RC | LR MC |
|-----------|------------------|-------------|--------|--------|-------|-------|
| 20110303  | Random           | 0.100%      | 0.100% | 0.080% | 0.100%| 0.100%|
|           | Mikro            | 0.030%      | 0.030% | 0.030% | 0.030%| 0.030%|
|           | Small            | 0.130%      | 0.130% | 0.130% | 0.120%| 0.110%|
|           | High             | 0.080%      | 0.080% | 0.080% | 0.080%| 0.080%|
|           | **Average**      | 0.085%      | 0.085% | 0.080% | 0.083%| **0.080%**|
| 20110306  | Random           | 0.100%      | 0.100% | 0.080% | 0.100%| 0.100%|
|           | Mikro            | 0.030%      | 0.030% | 0.030% | 0.030%| 0.030%|
|           | Small            | 0.120%      | 0.120% | 0.120% | 0.120%| 0.110%|
|           | High             | 0.080%      | 0.080% | 0.080% | 0.080%| 0.080%|
|           | **Average**      | 0.080%      | 0.083% | **0.078%** | 0.083%| **0.080%**|
| 20110309  | Random           | 0.110%      | 0.110% | 0.090% | 0.110%| 0.110%|
|           | Mikro            | 0.030%      | 0.030% | 0.030% | 0.030%| 0.030%|
|           | Small            | 0.130%      | 0.130% | 0.130% | 0.120%| 0.120%|
|           | High             | 0.090%      | 0.090% | 0.090% | 0.090%| 0.090%|
|           | **Average**      | 0.090%      | 0.090% | **0.085%** | 0.088%| **0.088%**|
| 20110325  | Random           | 0.100%      | 0.100% | 0.080% | 0.100%| 0.100%|
|           | Mikro            | 0.030%      | 0.030% | 0.030% | 0.030%| 0.030%|
|           | Small            | 0.120%      | 0.120% | 0.120% | 0.110%| 0.120%|
|           | High             | 0.080%      | 0.080% | 0.080% | 0.080%| 0.080%|
|           | **Average**      | 0.083%      | 0.083% | **0.078%** | 0.078%| **0.083%**|
| 20110403  | Random           | 0.100%      | 0.100% | 0.080% | 0.100%| 0.100%|
|           | Mikro            | 0.030%      | 0.020% | 0.020% | 0.020%| 0.030%|
|           | Small            | 0.120%      | 0.120% | 0.120% | 0.110%| 0.110%|
|           | High             | 0.090%      | 0.090% | 0.090% | 0.080%| 0.080%|
|           | **Average**      | 0.085%      | 0.083% | **0.078%** | 0.078%| **0.080%**|
| 20110409  | Random           | 0.110%      | 0.100% | 0.080% | 0.100%| 0.100%|
|           | Mikro            | 0.030%      | 0.030% | 0.030% | 0.030%| 0.030%|
|           | Small            | 0.120%      | 0.120% | 0.120% | 0.120%| 0.120%|
|           | High             | 0.090%      | 0.090% | 0.090% | 0.080%| 0.080%|
|           | **Average**      | 0.088%      | 0.085% | **0.080%** | 0.083%| **0.083%**|
| 20110411  | Random           | 0.100%      | 0.100% | 0.080% | 0.100%| 0.100%|
|           | Mikro            | 0.030%      | 0.030% | 0.030% | 0.020%| 0.030%|
|           | Small            | 0.120%      | 0.120% | 0.120% | 0.110%| 0.120%|
|           | High             | 0.090%      | 0.090% | 0.090% | 0.080%| 0.080%|
|           | **Average**      | 0.085%      | 0.085% | **0.080%** | 0.078%| **0.083%**|
| 20110412  | Random           | 0.100%      | 0.100% | 0.080% | 0.100%| 0.100%|
|           | Mikro            | 0.030%      | 0.030% | 0.030% | 0.030%| 0.030%|
|           | Small            | 0.120%      | 0.120% | 0.120% | 0.110%| 0.120%|
|           | High             | 0.090%      | 0.090% | 0.090% | 0.080%| 0.080%|
|           | **Average**      | 0.085%      | 0.085% | **0.080%** | **0.080%** | **0.083%**|
### Table 5. SLA Violation (SLAV) in all variant instance VM

| Workload  | Type Vm Instance | LR FuMAEVMS | LR CFS | LR MMT | LR RC | LR MC |
|-----------|------------------|-------------|--------|--------|-------|-------|
|           |                  | 20110303    |        |        |       |       |
|           | Random           | 0.0069%     | 0.0069%| 0.0046%| 0.0074%| 0.0068%|
|           | Mikro            | 0.0008%     | 0.0008%| 0.0008%| 0.0008%| 0.0008%|
|           | Small            | 0.0106%     | 0.0106%| 0.0106%| 0.0100%| 0.0096%|
|           | High             | 0.0039%     | 0.0039%| 0.0039%| 0.0037%| 0.0038%|
|           | Average          | 0.0055%     | 0.0055%| **0.0049%**| 0.0055%| 0.0053%|
|           |                  | 20110306    |        |        |       |       |
|           | Random           | 0.0066%     | 0.0066%| 0.0047%| 0.0069%| 0.0066%|
|           | Mikro            | 0.0008%     | 0.0008%| 0.0008%| 0.0008%| 0.0008%|
|           | Small            | 0.0098%     | 0.0098%| 0.0098%| 0.0099%| 0.0098%|
|           | High             | 0.0038%     | 0.0038%| 0.0038%| 0.0038%| 0.0038%|
|           | Average          | 0.0052%     | 0.0052%| **0.0048%**| 0.0053%| 0.0053%|
|           |                  | 20110309    |        |        |       |       |
|           | Random           | 0.0082%     | 0.0083%| 0.0061%| 0.0088%| 0.0087%|
|           | Mikro            | 0.0008%     | 0.0009%| 0.0009%| 0.0008%| 0.0008%|
|           | Small            | 0.0111%     | 0.0111%| 0.0111%| 0.0106%| 0.0108%|
|           | High             | 0.0048%     | 0.0048%| 0.0048%| 0.0050%| 0.0050%|
|           | Average          | 0.0062%     | 0.0063%| **0.0057%**| 0.0063%| 0.0063%|
|           |                  | 20110325    |        |        |       |       |
|           | Random           | 0.0072%     | 0.0072%| 0.0050%| 0.0074%| 0.0075%|
|           | Mikro            | 0.0008%     | 0.0008%| 0.0008%| 0.0007%| 0.0008%|
|           | Small            | 0.0097%     | 0.0097%| 0.0097%| 0.0095%| 0.0097%|
|           | High             | 0.0043%     | 0.0043%| 0.0043%| 0.0042%| 0.0042%|
|           | Average          | 0.0055%     | 0.0055%| **0.0049%**| 0.0055%| 0.0055%|
|           |                  | 20110403    |        |        |       |       |
|           | Random           | 0.0071%     | 0.0070%| 0.0047%| 0.0073%| 0.0072%|
|           | Mikro            | 0.0008%     | 0.0008%| 0.0008%| 0.0008%| 0.0008%|
|           | Small            | 0.0105%     | 0.0105%| 0.0105%| 0.0098%| 0.0099%|
|           | High             | 0.0043%     | 0.0043%| 0.0043%| 0.0042%| 0.0041%|
|           | Average          | 0.0057%     | 0.0056%| **0.0050%**| 0.0055%| 0.0055%|
|           |                  | 20110409    |        |        |       |       |
|           | Random           | 0.0075%     | 0.0072%| 0.0047%| 0.0075%| 0.0072%|
|           | Mikro            | 0.0008%     | 0.0008%| 0.0008%| 0.0008%| 0.0008%|
|           | Small            | 0.0104%     | 0.0104%| 0.0104%| 0.0104%| 0.0101%|
|           | High             | 0.0046%     | 0.0046%| 0.0046%| 0.0045%| 0.0045%|
|           | Average          | 0.0058%     | 0.0057%| **0.0051%**| 0.0058%| 0.0056%|
|           |                  | 20110411    |        |        |       |       |
|           | Random           | 0.0074%     | 0.0073%| 0.0049%| 0.0078%| 0.0075%|
|           | Mikro            | 0.0008%     | 0.0008%| 0.0008%| 0.0008%| 0.0008%|
|           | Small            | 0.0106%     | 0.0106%| 0.0106%| 0.0098%| 0.0102%|
|           | High             | 0.0045%     | 0.0045%| 0.0045%| 0.0045%| 0.0045%|
|           | Average          | 0.0058%     | 0.0058%| **0.0052%**| 0.0057%| 0.0057%|
|           |                  | 20110412    |        |        |       |       |
|           | Random           | 0.0072%     | 0.0070%| 0.0047%| 0.0074%| 0.0076%|
|           | Mikro            | 0.0009%     | 0.0008%| 0.0008%| 0.0009%| 0.0009%|
|           | Small            | 0.0102%     | 0.0102%| 0.0102%| 0.0100%| 0.0104%|
|           | High             | 0.0049%     | 0.0049%| 0.0049%| 0.0048%| 0.0047%|
|           | Average          | 0.0058%     | 0.0057%| **0.0052%**| 0.0058%| 0.0059%|
VM selection, and perform similar SLATAH performance with CFS. The best SLATAH performance in this research has achieved by MMT VM selection that provides FuMAEVMS in second position. FuMAEVMS will give energy efficiency in cloud data center and keep the performance of server with less time overload condition. This condition has showed the method not only consider the improvement performance efficiency but also try to give less percentage of time consuming host in overload condition as seen in Figure 2.

However, in Figure 3, FuMAEVMS has showed higher total average performance degradation during migration compared with all VM selection model. In Table 4, FuMAEVMS has showed bad PDM in overall condition VM instances. The condition could occur, because during migration process the proposed model unable calculate VM that have less time to migrate. The proposed model only considers variable Ram VM and Mips VM, which is not consider available physical machine bandwidth that required when migrating VM. Those conditions lead to the higher performance during migration.

The proposed model still has limitation to improve overall SLA performance in cloud data center that showed higher SLA Violation SLAV in Table 5. The results have realized as consequence in optimizing energy efficiency in cloud datacenter that caused bad performance SLA as it tradeoff. This results also occurs in the experiment that conducted by Beloglazov. The drawback in FuMAEVMS that perform bad degradation performance during migration gives direct impact to SLAV performance. Since SLA violation SLAV is the combination performance metrics between PDM and SLATAH. As results the total average of performance SLAV in this research has not given significant improvement compared with existing VM selection MMT,
6. Conclusions

This paper proposed a novel VM selection model, FuMAEVMS, in dynamic VM consolidation that can enable energy consumption in cloud data centers. FuMAEVMS combines Fuzzy Logic and Markov Normal Algorithm with Existing VM selection. Fuzzy logic is applied to categorize attributes of candidate VMs that should be migrated to overloaded hosts. Benefits of categorizing attributes of VMs have given possibilities of Markov Normal Algorithm in generating simple implication rules to decide which existing VM selection such as CFS, MMT, and MC should be used. After that, the existing VM selection was used to select candidate VMs that will be migrated from overloaded hosts.

The proposed VM selection model has been evaluated using Cloudsim with real workload datasets from CoMon PlanetLabs. FuMAEVMS has shown significant improvement in energy efficiency in cloud data centers compared to previous VM selection such as RC, MMT, and MC. Moreover, FuMAEVMS can reduce time consumption of hosts in overload conditions or known as SLA time per active host SLATAH, which is better than RC and MC.

In the other hands, since the focus in this research is to improve energy efficiency in cloud data centers, it gives drawbacks in performance of SLA violation. The proposed VM selection FuMAEVMS still has limitations in reducing performance degradation during migration PDM compared to existing VM selection. Due to the PDM result, it was given impact to the higher SLA violation SLAV when compared to existing VM selection. However, SLAV performance of proposed VM selection is still acceptable since the results are closed with CFS, RC, and MC. In future work, we would like to reduce the performance degradation during migration PDM to achieve minimum SLAV, and implement the proposed VM selection model as an add-on in OpenStack-Neat.

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