# Modified Best Fit Decreasing Method for optimum Power Consumption in Cloud Data Centers

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## Abstract

Cloud computing has revolutionized information and communication technologies. It has enabled computing resource provisioning based on demand and services. Large sets of computing nodes established around the world are connected to large scale data centres with mission critical computing infrastructure. The data centres operate round the clock transforming IT industry. Automata approach was adopted to arrive at an energy efficient algorithm by comparing the Dynamic Voltage and Frequency Scaling (DVFS) and Modified Best-Fit Decreasing method (MBFD). Utilisation of memory, network bandwidth and Central Processing Unit were considered as performance parameters for evaluation of power consumption. Efficiency of the cloud was estimated by considering minimum energy and minimum correlation coefficient. Multi correlation coefficient method was used to estimate the power aware energy efficiency. Modified best-fit decreasing method showed decreased power consumption by 20% to 25% than that of the existing best-fit decreasing method considering varying memory, bandwidth and MIPS.

***Keywords:*** *Virtual Machine, Modified Best Fit Decreasing Method, Cloud computing*

## 1.0 Introduction

Cloud computing is a way of computing the data residing inside the servers which are remotely placed in different locations. The data can be accessed from any part of the world. Wide adoption of cloud technology in IT and other sectors resulted in high energy consumption in servers [1]. There has been a significant increase in the number of data centres across the globe. Social networking media consume huge power, a large proportion of which is wasted in idle state [3-5]. As the server responds to the clients' requests it consumes high power, which is limited in supply [2]. The other user's host which is available in the VM can be migrated to some other VM which is having space to provide the services. During the idle state the

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power can be saved by switching off the server in the data centre [6]. Dynamic voltage frequency scaling learning automata approach is used to reduce the power consumption by shutting down the instances during idle time of the server [7].

## 2.0 Power Management

Power management employs dynamic and static techniques implemented on application and hardware levels. The optimization approaches at design stage in different times and dynamic techniques are implemented in various algorithms [8]. These techniques are included at hardware level specification and the resources which are available in the cloud.

The resources and specifications on the design technique algorithms considered during the run time of an applications [9]. The dynamic configured algorithms save the energy in the data centre during an idle time of the server. The servers can be deactivated and save the energy on the workload condition. In the data centre the idle servers consumes more power and hardware resources [10]. Even the light weighted applications consume large amount of energy during under-loaded conditions.

The virtualization technology, heterogeneity of resources and correlation infrastructure running on the same virtual machine in the data centre help to reduce the power consumption. Due to the lack of resources availability in the data centre the Physical machine performance on the data centre through virtualization is the solution for the light weighted and idle server's application deployment in cloud [11, 12]. Virtualization technology improves the productivity and hardware resources utilizable in the data centre.

The benefit from virtualization technology is the movement of VM from one physical host to another without affecting the performance. The process of VM movement is called as live migration. While the movement of VM forms one host to another host the resources considered as CPU, bandwidth and RAM [13]. The VMs allotted are limited in each servers based on the capacity. The lower productivity of VMs on PMs which is running can be moved to another PM which is having the high productivity of VM consolidation. During this process, the idle servers are in the rest position which will go to sleep mode and increase the efficiency in the cloud data centre [14, 15]. When the small number of VMs and PMs are in the data centre the movement is easy and consolidation is easy. If the number of VM and PM increased to more than 500 then the situation is unpredictable and the automation is becoming is necessary [16, 17]. The evaluation of number of VM and PM consolidation can be calculated using the equation 1.

$$\textit{(Total Number of PMs)}^{\textit{(Total Number of VMs)}} \tag{1}$$

During the large set of placement and VM to PM mapping in brute force is to find nearest optimal plan in VM consolidation in the data centre.

The parameters can be described as

- M- Number of Physical machines available.
- N- Number of VM to place in PM.
- Finding the VM to PM mapping in the data centre.

The parameters considered as CPU utilization, memory and networking components.

## 3.0 Learning Automata

The minimal number of actions performs in Learning Automata (LA). In the random selection the action can be accessed within the environment [12]. The automata responses for the actions based on the selected action. In the Fig. 1 describes the relationship between LA and Environment Variables (EV).

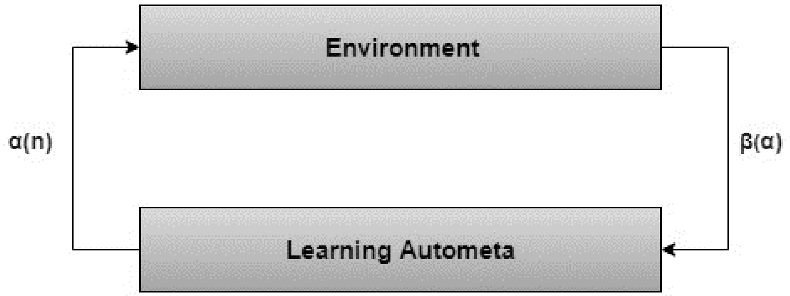


**Fig. 1.** Learning Automata and Environment Variable

The automata structures can be described in piece as

LA= {α, ß, P, Q, R}

$\alpha = \{\alpha_1, \alpha_2, \alpha_3, \text{------}\alpha_n\}$ set of action performances in LA

$ß = \{ß_1, ß_2, ß_3, \text{-------}ß_m\}$ set of input

$P = \{p_1, p_2, p_3, \text{-------}p_r\}$ Action performance

Q = P(r+1) = Q [α (n), ß (n), p (n)]

$R = \{R_1, R_2, R_3, \text{-------}R_n\}$ action possibility in any conditions

In the learning automata the action chosen is $\alpha_i$ then the environment give a favourable response to the automata. If $P_i(r)$ is increases the performance then the probabilities decreases in the environment. With the improved response of $P_i(r)$ decreases then the probabilities in the environment increase. In all the above environment, variable changes are the sum of $P_i(r)$, others will remain constant.

(i) Favourable responses can be defined as

$$P_i(r+1) = P_i(r) + \alpha\,[1- P_i(r)]$$

$$P_j(r+1) = (1- \lambda)\, P_j(r)\ € \ jj \neq I \qquad (2)$$

(ii) Favourable response with an action made can be defined as

$$P_i(r+1) = (1- \lambda)\, P_i(r)$$

$$P_j(r+1) = \lambda/n-1 + (1- \lambda)\, P_j(r)\ € \ jj \neq I \qquad (3)$$

In the equation 2, we depict that the number of VMs increased is considered and decrease the probability status based on the workload condition is analyzed. In the equation 3 findings the decrease of probability and increase the total number of VMs is considered to identify the workload condition in the data centre. The equation 2 and equation 3 is used to calculate $\lambda$ penalty and is discussed in further equations.

## 4.0 Multiple Correlation Coefficients (MCC)

The study of MCC is considered for more than two variables. Dependent variables and Independent variables are considered. Among the information between the variables positive correlation is considered. The environment variable MCC is used to assign dependent variables in the quality analysis prediction of multiple regression models. The values depend on the predicted value and the dependent variables correspond to real data considered in the data centre [18].

The dependent variables depict the value x is considered as results of the variables: y1, y2, y3, y4. The observation from regression relation is shown in i from x variable to Q shown in Equation 4.

$$X_i=ß_0+ß_1y_{1i}+\text{-----}+ß_qy_{rp}+e_i \qquad (4)$$

In equation 5.4, $X_i$ is defined for i values considered as dependent variable.

Q is the total number of predictions in sum.

Jis the coefficients whereas j = 0, 1,------, q.

$e_i$are the observed values from i in different cases.

Suppose y is the matrix of N*(Q+1),

Whereas always first column considered with 1.

The data considered from various collection from the independent variables is considered as x vector. It is calculated as 1*N forms the real dependent variable.

The x and y value coordinates in the matrix is considered as

$$X= x1, x2, x3 ----x_n \tag{5}$$

$$y= 1-------y_{ip}, 1-------y_{np} \tag{6}$$

The equation 5 & 6 defined as the set of variables and set of covariant in column matrix. The dependent variable x is shown as $\hat{x}$ and which is predicted the vector values shown in equation 7

$$\begin{aligned} \hat{x} &= y.a \\ a &= \left(yy^m\right)^{-1} y_x^m \end{aligned} \tag{7}$$

Whereas $y^T$ defines as the transposed of y matrix. The accessed quality value is calculated and prediction by MCC which can be calculated through linear relationship with its values as Zero and One. The description is shown in equation 8.

$$R^2_{x.1.......Q} = \left[\frac{Co\,\mathrm{var}\,ience(x_i,\hat{x})}{\sqrt{\mathrm{var}(x_i)\mathrm{var}(\hat{x})}}\right] \tag{8}$$

The covariance of the regression can be calculated in equation 8 and correlation between the variables calculations shown in the equation 9.

$$R^2_{X.1........Q} = \left[\frac{\sum_1^n (x_i - m_x)^2 (\hat{x}_1 - n_{\hat{x}})^2}{\sum_1^n (x_i - m_x)^2 \sum_1^n (\hat{x}_i - m_{\hat{x}})^2}\right] \tag{9}$$

In the equation 9 the correlation between the covariance calculations is addressed. It can be calculated between VM and the collection VMs selected in different physical machines. The matrix y depicts the productivity of VMs in the cloud and all the column matrix includes M to N productivity with history of VM selected host in the server.

## 5.0 Proposed Efficient Power Model and MBFD Algorithm

The CPU, storage devices, cooling systems and memory are the components consumes power in the data centre. The model accurately defined as the linear relationship among the utilization of CPU and power consumption in the data centre [19, 20]. The real data of CPU utilization and power consumption from SPEC benchmark data is tested.

**Table 1.** Hardware Specifications of MBFD Setup

| | |
|---|---|
| Server 1 | HP ProLiant ML110 G4 (Intel Xeon 3040, 2 cores × 1860 MHz, 4 GB), |
| Server 2 | HP ProLiant ML110 G5 (Intel Xeon 3075, 2 cores × 2660 MHz, 4GB). |

In the Table 1 shows the hardware specification configurations are considered to test our environment variables in cloud environment.

**Algorithm: Modified Best Fit Decreasing (MBFD) Algorithm**

In the MBFD Algorithm the actions performed in automata is considered for total number of hosts. The automata are allowed to perform only one active (candidate) host at a time.

P [I] – Probability of host selected in array

A - Is the primary value which stats from 1

I – Selected host ID

Step 1: Select the candidate list from VM Resources (Not overloaded)

Step 2: VM host is obtain from the selection

Step 3: Power is estimated based on the selection of candidate host

Step 4: Relationship between the energy and CPU usage is used to estimate the energy efficiency

Step 5: Accepted host and rest of VMs energy is compared and analyzed the results

Step 6: Correlation process is adopted in the current VM and other hosts

Step 7: If the current host in VM has minimum correlation and energy

Step 8: Then reward to automation

Step 9: Steps are repeated to number of hosts based on the host is selected

Step 10: Highest priority host is selected for destination host

In the HSC algorithm the overloaded host successive probability increases. The probability reduces based on the choice of the host selection. The differences are identified through the rest of the hosts which is available with resources.

## 6.0 Implementation and Results

Here we use the selection policy through Thresholds (THR) value to identify the overloaded hosts in the cloud. Minimum Migration Time (MMT) policy used to select the VM from the resources. Here we consider the 0.98 error confidence level. The obtained results are compared with DVFS method from Beloglazov [21]. The results are shown in Fig. 2.

**Table 2.** Energy Consumption Comparison between DVFS and MBFD

| Number of VM | Energy Consumption (KW) | |
|---|---|---|
| | DVFS | MBFD |
| 10 | 600 | 564 |
| 32 | 530 | 523 |
| 48 | 700 | 634 |
| 64 | 863 | 823 |
| 89 | 965 | 950 |
| 102 | 996 | 995 |
| 126 | 1065 | 1030 |
| 149 | 1234 | 1220 |
| 170 | 1432 | 1423 |

In Table 2 we show the total number of virtual machine considered for the experiment against the energy consumption in KW compared with DVFS and MBFD methods.

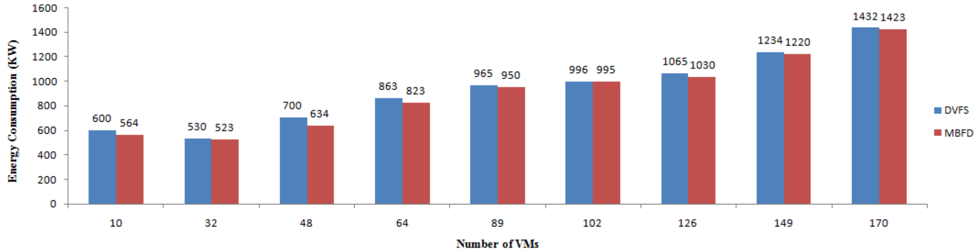


**Fig. 2.** Energy Consumption in two different approaches

## 6.0 Conclusion

The High energy consumption in the data centre causes more Co2 emission in the environment. Now a day's cloud computing energy efficiency and reduce the power consumption is the hot technology in the research. In this chapter VM selection policy implemented on CloudSim tool to reduce power utilization in the data centre. The power-aware energy efficiency is automated by considering the number of physical host machines and double the number of virtual machines considered with different workload conditions which includes memory usage and the bandwidth. The automata approach, minimum energy and minimum correlation coefficient are the two parameters considered to find the efficiency in cloud. Multi correlation coefficient method is used to find the power aware energy efficiency in the cloud environment the learning automata is one of the best approach is used to find the efficiency in the cloud. Our experimental result shows the comparison of DVFS and MBFD method and The Modified best-fit decreasing method is accurate to reduce the power consumption 20% to 25% less than the existing best-fit decreasing method by varying the parameters of memory, bandwidth and MIPS.

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