

## ENTROPY BASED METHOD TO CALCULATE WEIGHT FOR MULTI-CRITERIAN VM ALLOCATION POLICY IN COMPUTE CLOUD

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ABSRACT: Cloud computing is an attractive IT infrastructures for managing automatic optimum resource management as well as modern service delivery models. This paper will apply Entropy Weight method and TOPSIS power and SLA method to find the physical machine. This policy computes the scores of all the PMs that are capable for hosting a VM and selects the PM with the highest score. VM allocation based on the multicriteria is an efficient way for the optimal allocation weightage to each criteria will define priority to that parameter. Random weight will not justify the priority to the different parameter and entropy weighted method to generate the weightage based on the criterian considered for allocation. This method namely entropy weighted TOPSIS power and SLA Allocation policy that optimize energy consumption, number of VM migration and SLA violation.

KEYWORD: Entropy weight method, TOPSIS method, VM migration, SLA Violation, energy consumption

#### I. INTRODUCTION

Cloud computing is the distributed computing model which provides computing facilities and resources to the end users in an on-demand pay-as-you-go model [1]. Cloud computing brings modern technologies together to provide a vast range of service types for diverse users. Cloud computing is the use of cloud resources (hardware and software) that are delivered as a service over a network (typically the Internet) [2].Cloud provides a managed pool of resources which includes storage, processing power and software services [3].

The Virtualization of cloud computing allows multiple VMs to run on the single physical machine. it is an enabling technology used to reduce the energy consumption of data centers [5]the idea is to identify the underloaded PMs and to migrate its VMs to other appropriate PMs. By working underloaded PMs free, they can be further shutdown and thus, energy consumption can be reduced. The basic consolidation approach in cloud data centers are divided into four sections i) determination of under-loaded hosts ii)determination of overloaded hosts iii) selection of VMs that should be migrated from an overloaded hosts iv)finding a new placement of selected VMs for migration from the overloaded and underloaded hosts[6].

Appropriate VM placement policy is required for efficient resource utilization. By separating the virtual machines (VMs) from under-loaded physical machine (PM) of data center and allowing to place it on PM where energy consumption improves. This approach is called as Virtual Machine Consolidation. The VMs are consolidated into a limited subset of physical resources. So the remaining idle nodes are switched to low power consumption modes or turned-off which reduces the energy consumption [7].

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In general, Multi-Criteria Decision Making (MCDM) problems are frequently evaluated. To solve problems related to decision making, several optimization methods are used in practice. In this paper we focused an appropriate way to select PMs for VM placement for the same, multiple criteria are chosen for selection of PMs

Among many famous MCDM methods, Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is a practical and useful technique for ranking and selection of a number of possible alternatives through measuring Euclidean distance [4]. It bases upon the concept that the chosen alternative should have the shortest distance from the positive ideal solution (PIS), i.e., the solution that maximizes the benefit criteria and minimizes the cost criteria; and the farthest from the negative ideal solution (NIS), i.e., the solution that maximizes the cost criteria and minimizes the benefit criteria.

In typical multiple criteria decision making (MCDM) approaches, weights of attributes reflect the relative importance of decision making process. Because the evaluation of criteria entails diverse opinions and meanings, we cannot assume that each evaluation criterion is of equal importance [7] there are two categories of weighting methods: subjective methods and objective methods. The fuzzy methods are to determine weights solely according to the preference or judgments of decision makers. Then apply some mathematical methods such as the eigenvector method, weighted least square method, and mathematical programming models to calculate overall evaluation of each decision maker. The entropy weighted methods determines weights by solving mathematical models automatically without any consideration of the decision maker's preferences.

This paper proposes multicriteria algorithms based on TOPSIS (Technique for an order of preference by similarity to ideal solution) [5] for finding the best score to physical machine based on criteria. This algorithm optimize energy consumption, SLA Violation and number of VM Migration

The Main contribution of this paper

• Proposing a novel multicriteria resource allocation method namely entropy weighted TOPSIS power and SLA Allocation policy that optimize energy consumption, number of VM migration and SLA violation.

This paper is organized as follows. Section II presents related work. Section III presents system model and proposed policy. Section IV concludes the paper.

#### II. RELATED WORK

The authors in [5] have proposed enhanced optimization (EO) policy as a novel resource management procedure in cloud data centers. The main idea behind EO policy is solving the resource allocation problem for the VMs that are selected to be migrated from either overloaded or underloaded PMs. Besides, they have introduced a solution based on the Technique for Order of Preference by Similarity to ideal solution (TOPSIS) for optimizing different targets in clouds data centers at the same time including energy consumption, SLA violation, and a number of VM migrations. Based on this idea, they have proposed TOPSIS power and SLA Aware Allocation (TPSA) and TOPSIS –available capacity –number of VMs-Migration Delay (TACND) policies as novel multicriteria algorithms for resource allocation and determination of underloaded PMs in cloud data centers, respectively.

The authors in [6] have conducted competitive analysis and proved competitive ratios of optimal online deterministic algorithms for the single VM migration and dynamic VM consolidation problems. They have divided the problem of dynamic VM consolidation into four parts: (1) determining when a host is considered as being overloaded; (2) determining when a host is considered as being underloaded; (3) selection of VMs that should be migrated from an overloaded host; and (4) finding new placement of the VMs selected for migration from the overloaded and underloaded hosts. They have proposed the novel adaptive heuristics for all parts. They have used Power Aware Best Fit Decreasing (PABFD) algorithm to solve resource allocation problem in the fourth part which is similar to Modified Best Fit Decreasing (MBFD) policy.



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The author [7] proposes to extend the TOPSIS to the fuzzy environment. Owing to vague concepts frequently represented in decision data, the crisp value are inadequate to model real-life situations. In this paper, the rating of each alternative and the weight of each criterion are described by linguistic terms which can be expressed in triangular fuzzy numbers. Then, a vertex method is proposed to calculate the distance between two triangular fuzzy numbers. According to the concept of the TOPSIS, a closeness coincident is denied to determine the ranking order of all alternatives by calculating the distances to both the fuzzy positive-ideal solution (FPIS) and fuzzy negative-ideal solution (FNIS) simultaneously

Author [9] proposes a multi-attribute group decision-making (MAGDM) based scientific decision tool to help firms to judge which cloud computing vendor is more suitable for their need by considering more comprehensive influence factors. It is argued that objective attributes, i.e., cost, as well as subjective attributes, such as TOE factors (Technology, Organization, and Environment) should be considered for the decision making in cloud computing services, and presents a new subjective/objective integrated MAGDM approach for solving decision problems. The proposed approach integrates statistical variance (SV), improved techniques for order preference by similarity to an ideal solution (TOPSIS), simple additive weighting (SAW), and Delphi-AHP to determine the integrated weights of the attributes and decision-makers (DMs). The method considers both the objective weights of the attributes and DMs, as well as the subjective preferences of the DMs and their identity differences, thereby making the decision results more accurate and theoretically reasonable.

Author [10] multiple criteria decision making (MCDM) is widely used in ranking one or more alternatives from a set of available alternatives with respect to multiple criteria. Inspired by MCDM to systematically evaluate alternatives under various criteria, we propose a new fuzzy TOPSIS for evaluating alternatives by integrating using subjective and objective weights. Most MCDM approaches consider only decision maker's subjective weights. However, the end-user attitude can be a key factor. We propose a novel approach that involves end-user into the whole decision making process. In this proposed approach, the subjective weights assigned by decision makers (DM) are normalized into a comparable scale. In addition, we also adopt end-user ratings as an objective weight based on Shannon's entropy theory. A closeness coefficient is defined to determine the ranking order of alternatives by calculating the distances to both ideal and negative-ideal solutions. A case study is performed showing how the proposed method can be used for a software outsourcing problem. We provide decision makers more information to make more subtle decisions.

#### III. PROPOSED SYSTEM MODEL

#### **3.1 PROBLEM STATEMENT**

VM allocation based on the multicriteria an efficient way for the optimal allocation weightage to each criteria will define a priority to that parameter. Random weight will not justify the priority to the different parameter as it does not follow any appropriate method hence, it is required to the entropy weighted method to generate the weightage based on the criterian considered for allocation. In our previous work, weight to each criteria generated randomly.

#### **3.2 SYSTEM MODEL**

Discussed in our previous work[12], The System model contains cloud datacenters with heterogeneous resources for various users. The system model [1] in figure 1 has two important parts: i) central manager ii) agent. The central manager is the resource manager which allocates virtual machines to available hosts in cloud datacenters and also it resizes the virtual machines according to their needs on resources. The central manager decides when and which VMs should be migrated from PMs.

The agents are connected to the central manager through a network interface. Agents monitor PMs and send gathered information to the central manager.

Hypervisor performs actual resizing and VM migration. To provide Fault Tolerance (FT) and High Availability (HA) the central manager runs on any VMs instead of PMs.



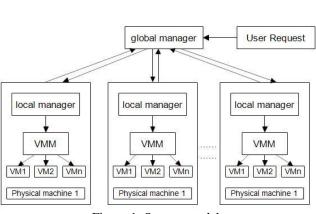


Figure 1: System model

#### **3.3 POWER AND ENERGY MODEL**

The power consumption with CPU utilization by a server can be approximated using linear relationship. This approximation comes from the idea that most of the power consumption in cloud data center is by CPU. The energy consumption is modelled by Anton Beloglazov in [6] as energy consumed is formulated as follows in the equation. That is the summation of power consumed during a period of time.

$$E(t) = \int p(t) \, \mathrm{d}t \tag{1}$$

#### **3.4 PROPOSED METHOD**

In our previous work[12], we have randomly generated the weights attached to score of each criterian .the random weight cannot justify the priority of objectives. hence it is required to identify the method that efficiency generates coefficient.

In proposed work, we identified a for to generate entropy weighted method using multicriteria decision making TOPSIS method.

#### STEP OF TOPSIS METHOD ARE AS FOLLOWS

Step 1: identify decision variable identify the evaluation criteria.

*Step 2:* to standardized decision matrix

Step 3: Construct the Positive Ideal Solution (PIS) and Negative Ideal Solution (NIS).

Step 7: Calculate the distance of each alternative from PIS and NIS respectively.

Step 5: Construct the weighted normalized decision matrix.

Step 8: According to the closeness coefficient, the ranking order of all alternatives can be determined.

Determining the weight of each index through **entropy weight method**, and the calculation process is as follows.

1) Calculating the proportion " $P_{ij}$ " of the index value of project i under index j: " $P_{ij}$ " is calculated as in (3).

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{3}$$

2) Calculating the entropy " $e_j$ " of index j: " $e_j$ " is calculated as in (4).

$$e_{j=-k} \sum_{i=1}^{m} p_{ij} \ln p_{ij}$$
(4)

The "k" in (4) can be calculated in (5),

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(5)

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where,

 $k = 1/\ln m$ .

m= number of row,n=number of columm

3) Calculating the entropy weight "wj" of index j: "wj" is calculated as in (6).

$$W_j = \frac{(1-e_j)}{\sum_{i=1}^n (1-e_j)}$$
(6)

**3.4.1 Proposed TOPSIS power and SLA based VM allocation (TPSA) approach using entropy weights** EWTPSA (Entropy Based Weight TPSA Policy) is a multi-objective resource allocation method to identify solutions from a finite set of alternatives based upon simultaneous distance minimization from an ideal point and distance maximization from a nadir point [5] we introduced Entropy weighted TOPSIS method as is to apply different weights for the criteria defined in Table 1. It will be useful to reduce for fulfilling different objectives including energy consumption, SLA violation, and number of VM migrations

		Table-1: considered crit	teria in PSW I policy.
No.	Notation	Parameter	Description
1	PI	Power increase	Power increase of allocating a VM on a PM
2	AV	Available capacity	Available resource capacity of a PM
3	NV	Number of VMs	Number of VMs on PM
4	RC	Resource correlation	Resource correlation of a VMs with the VMs on a
			PM
5	MD	Migration delay	The delay incurred due to migration of VMs to PM
6	RU	Resource utilization	Utilize the resource of a PM
7	SLAV	SLA violation	Service level agreement agreed between the
			service provider and the service consumer

 EWTPSA policy takes advantage of TOPSIS as a multi-criteria algorithm that considers seven criteria depicted in Table 1 in its decision process. This policy computes the scores of all the PMs that are the candidate for hosting a VM using the method that is described in this section and selects the PM with the highest score. Criteria considered in EWTPSA policy can have either benefit or cost type. The more the value of criteria with the benefit type, and the lower the value of criteria with the cost type, the closer is the answer to the optimum point. EWTPSA computes the score of PMs with the following consideration (1) the selected PM with least

power increase, (2) the selected PM with most available maximum capacity, (5) the selected PM with least number of VMs, (6) VMs on the selected PM have the least resource correlation with the VM to be allocated, (7) the migration delay of the VM to be allocated to the selected PM is the least, and (8) the selected PM with least resource utilization after placing the migrating VM on it.

Applying resource correlation in TPSA policy is based on the idea that the higher the correlation between applications that use the same resources on an oversubscribed server, the higher probability the server to become overloaded [6]. The correlation of a VM to be allocated by the VMs hosting on a PM is calculated using the multiple correlation coefficient [6]. It is used in multiple regression analysis to assess the quality of the prediction of the dependent variable. Consider X1, X2, ..., Xm to be m random variables representing the CPU utilization of m VMs hosting on a PM and Y to be the CPU utilization of the VM to be allocated. Then variable Y is dependent and m random variables are independent. We want to assess the level of the correlation between Y and m random variables. As shown in Eq. (9), we define X as the  $m \times n$  augmented matrix containing the observed values of the m independent random variables, and y as the  $n \times 1$  vector of Y observations.[6]



Rajeshvari Panchal *et al*, International Journal of Computer Science and Mobile Applications,<br/>Vol.6 Issue. 4, April- 2018, pg. 170-182ISSN: 2321-8363<br/>UGC Approved Journal<br/>Impact Factor: 5.515 $\begin{bmatrix} 1 & x_{1,1} \cdots & x_{1,n} \\ \vdots & \ddots & \vdots \\ 1 & x_{m,1} \cdots & x_{m,n} \end{bmatrix}$  $\begin{bmatrix} y1 \\ \vdots \\ yn \end{bmatrix}$ (7)

 $\hat{y}$  is defined as a vector of predicted values of the dependent random variable Y and is computed using Eq. (8).

$$\hat{y} = Xb, \quad \hat{y} = (X^T b)^{-1} X^T y[6]$$
 (8)

All the information assigned to the PMs in the time slot t from a decision matrix PMC (physical machine configuration) as shown in figure

PI <sub>PM1</sub>	AC <sub>PM1</sub>	RU <sub>PM1</sub>	NV <sub>PM1</sub>	RC <sub>PM1</sub>	MD <sub>PM1</sub>	SLAV <sub>PM1</sub>
PI <sub>PMi</sub>	AC <sub>PMi</sub>	RU <sub>PMi</sub>	NV <sub>PMi</sub>	RC <sub>PMi</sub>	MD <sub>PMi</sub>	SLAV <sub>PM1</sub>
PI <sub>PMN</sub>	AC <sub>PMN</sub>	RU <sub>PMN</sub>	NV <sub>PMN</sub>	RC <sub>PMN</sub>	MD <sub>PMN</sub>	SLAV <sub>PM1</sub>

Where PM1, PM2....PMn are available PMs that are candidates for selection by TPSA; PI, AC, NV, RC, MD are the Five criteria.

Step1: following are the normalize the decision matrix PMC (Physical Machine Configuration) to have dimensionless decision matrix PMC. The decision matrix is made dimensionless by dividing each entry by the maximum value of each column according to below matrix.

PIPM1	ACPM1	RUPM1	NVPM1	RCPM1	MDPM1	SLAVPM1
PImax	ACmax	RUmax	NVmax	RCmax	MDmax	SLAVmax
PIPMi	АСРМі	RUPMi	NVPMi	RCPMi	MDPMi	SLAVPMi
PImax	ACmax	RUmax	NVmax	RCmax	MDmax	SLAVmax
PIPMN	ACPMN	RUPMN	NVPMN	RCPMN	MDPMN	SLAVPMN
PImax	ACmax	RUmax	NVmax	RCmax	MDmax	SLAVmax

Step2: In the next step,  $PM^+$  and  $PM^-$  are determined. In general, the criteria can be classified into two types: benefit and cost. The benefit criteria means that a higher value is better, while for the cost criteria is the opposite. Larger values for a benefit type attribute leads to less distance from PM+ and more distance from PM-, while opposite condition is cost type variable. AC is benefit type attribute and all other is cost type attribute. Then determining PM+ and PM-.Here for placement, place a VM on a PM that the PM has least power increase, the highest available capacity, least number of VMs, least resource correlation, and least migration delay.

 $PM+ = \{PI-, AC+, RU+, NV-, RC-, MD-, SLAV-\}$ 

PM- = {PI+, AC-, RU+, NV+, RC+, MD+, SLAV-}

Where criteria+ and criteria- are the maximum and minimum value in each column of the decision matrix.



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Step3: In this Step, the relative distance for each criteria of a PM from PM+ and PM- are calculated using below equation

Score = 
$$\frac{\sqrt{(PM_{criterian}^{j} - PM_{criterian}^{-})^{2}}}{\sqrt{(PM_{criterian}^{j} - PM_{criterian}^{-})^{2}}\sqrt{(PM_{criterian}^{j} - PM_{criterian}^{+})^{2}}}$$

Where Score  $(PM^{j})$  the score of a specific criterian of  $j^{th}$  PM.

Here, the weight is assigned to each criterian and is a score of PMs multiplied with a score to generate. Step4: To identify the optimize host we are using entropy weighted method of multi-objective optimization.it is the method of optimizing technique in which weights are assigned to score of each PMs

Score  $(PM^{j}) = \sum_{criterian=1}^{\#criterian} Weight_{criterian} * Score_{Criterian}^{PMj}$ 

Step5: Rank PMs according to their Score and select the one with the highest score. The PM with the highest score has the maximum distance from PM- and the Minimum distance from PM+

#### IV. Experimental Evaluation

#### 4.1 Example Scenario:

#### 4.1.1 Our Previous Work

Step1: The explanation of the example is carried out from the matrix as shown in table2.there are seven criteria and six PMs .we have considered two criteria in addition i.e. resource utilization and SLA violation as shown in table 2.seven criteria are PI, AC, NV, RC, MD, RU, SLAV in table 2.in order to select the best PM we go through the following steps:

Criterion	Power Increase	Available Capacity	Number of VMs	Resource Correlation	Migration Delay	Resource Utilization	SLA Violatio n
Physical Machines	PI(Watt)	AC (MIPS)	NV (Number)	RC (%)	MD (mS)	RU (%)	SLAV (%)
PM <sub>1</sub>	20	200	10	20	2.2	40	0.00125
PM <sub>2</sub>	30	300	8	25	0.75	28	0.00119
PM <sub>3</sub>	15	320	12	80	1.71	43.75	0.015873
PM <sub>4</sub>	20	800	5	90	2.88	54	0.009259
PM <sub>5</sub>	10	400	7	50	3.67	56.333	0.016789
PM <sub>6</sub>	15	500	9	70	2.44	52	0.010417

Table-2: Value of all criteria

Step2: All the criterian are divided by maximum value of each column.



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Criterion	Power Increase	Available Capacity	Number of VMs	Resource Correlation	Migration Delay	<b>Resource</b> utilization	SLA violatio n
Physical Machines	PI(Watt)	AC (MIPS)	NV (Number)	RC (%)	MD (mS)	RU (%)	SLAV (%)
$PM_1$	0.67	0.25	0.83	0.22	0.60	0.71	0.07
PM <sub>2</sub>	1.00	0.38	0.67	0.28	0.20	0.50	0.07
PM <sub>3</sub>	0.50	0.40	1.00	0.89	0.47	0.78	0.95
PM <sub>4</sub>	0.67	1.00	0.42	1.00	0.78	0.96	0.55
PM <sub>5</sub>	0.33	0.50	0.58	0.56	1.00	1.00	1.00
PM <sub>6</sub>	0.50	0.63	0.75	0.78	0.66	0.92	0.62

Table-3: All the criteria are divided by the maximum value of each column

**Step3**: PM+ are determined whose power increase least, the highest capacity, least number of VMs, least resource correlation, most resource utilization, least SLA violation and for PM- it is vice versa. We place VM on such PM+.

 $PM^+= \{PI^-, AC^+, NV^-, RC^-, MD^-, RU^+, SLAV^-\} = \{0.33, 1.00, 0.42, 0.22, 0.20, 0.50, 0.07\}$ 

 $PM^{-} = \{PI^{+}, AC^{-}, NV^{+}, RC^{+}, MD^{+}, RU^{-}, SLAV^{+}\} = \{1.00, 0.25, 1.00, 1.00, 1.00, 1.00, 1.00\}$ 

Step4: The relative distance for each criterian of a PM

Criterion	Power Increase	Available Capacity	Number of VMs	Resource Correlation	Migration Delay	Resource Utilization	SLA Violatio n
Physical Machines	PI(Watt)	AC (MIPS)	NV (Number)	RC (%)	MD (mS)	RU (%)	SLAV (%)
PM1	0.50	0.00	0.71	0.00	0.50	0.58	0.00
PM2	0.00	0.17	0.43	0.07	0.00	1.00	0.00
PM3	0.75	0.20	1.00	0.86	0.33	0.44	0.94
PM4	0.50	1.00	0.00	1.00	0.73	0.08	0.52
PM5	1.00	0.33	0.29	0.43	1.00	0.00	1.00
PM6	0.75	0.50	0.57	0.71	0.58	0.15	0.59

Table-4: find the score of each criterian

Step5: Modified PMC assigned to score of PMs and all the VM assigned the highest score of PM.

Case1: Existing Method with the same weight assigned (weight=0.2)



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Physical machine	PM1	PM2	PM3	PM4	PM5	PM6
Score	0.34	0.13	0.63	0.65	0.61	0.62

#### Table 5: existing method with the same weight assigned.

Case2: Proposed method with the Different weight assigned

Weight of	0.1028311	0.1467589	0.0470779	0.166789	0.119624	0.0328408	0.3840757
criteria	06	04	48	6	31	11	09

#### Table 6: proposed method with the different weight assigned.

Physical machine	PM1	PM2	PM3	PM4	PM5	PM6
Score	0.16	0.09	0.71	0.65	0.74	0.60

#### 4.1.2 Proposed Entropy weighed method

Now, we have examined the same example with entropy weight method, its evaluation is as below Step1: There are seven criteria and six PMs .we have considered two criteria in addition i.e. resource utilization and SLA violation as shown in table 2.seven criteria are PI, AC, NV, RC, MD, RU, SLAV in table 2.in order to select the best PM we go through the following steps:

			Table	7: criteria			
Criterion	Power Increase	Available Capacity	Number of VMs	<b>Resource</b> Correlation	Migration Delay	Resource Utilization	SLA Violatio n
Physical Machines	PI(Watt)	AC (MIPS)	NV (Number)	RC (%)	MD (mS)	RU(%)	SLAV(%)
$PM_1$	20	200	10	20	2.2	40	0.00125
PM <sub>2</sub>	30	300	8	25	0.75	28	0.00119
PM <sub>3</sub>	10	320	12	80	1.71	43.75	0.015873
PM <sub>4</sub>	20	800	5	50	2.88	54	0.009259
PM <sub>5</sub>	15	300	7	90	3.67	56.333	0.016789
PM <sub>6</sub>	10	500	9	70	2.44	52	0.010417

Step2: Calculating the proportion "pij" of the index value of project i under index j: "pij" is calculated



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Physical										
machine	PI	AC	NV	RC	MD	RU	SLAV			
PM1	0.19047619	0.082644628	0.196078431	0.059701493	0.161172161	0.145941193	0.02281938			
PM2	0.285714286	0.123966942	0.156862745	0.074626866	0.054945055	0.102158835	0.02172405			
PM3	0.095238095	0.132231405	0.235294118	0.23880597	0.125274725	0.15962318	0.289769616			
PM4	0.19047619	0.330578512	0.098039216	0.149253731	0.210989011	0.197020611	0.169027712			
PM5	0.142857143	0.123966942	0.137254902	0.268656716	0.268864469	0.205532631	0.306491657			
PM6	0.095238095	0.20661157	0.176470588	0.208955224	0.178754579	0.189723551	0.190167586			

Table 8:Normalize the matrix

Step 3:in order to find  $e_j$  we calculate Pij \*  $lnP_{ij}$ 

PHYSICAL							
MACHINE	PI	AC	NV	RC	MD	RU	SLAV
PM1	-	-	-	-	-	-	-
	0.3158529	0.2060500	0.3194589	0.1682625	0.2941846	0.2808713	0.0862605
	67	37	29	83	71	46	68
PM2	-	-	-	-	-	-	-
	0.3579322	0.2588107	0.2905700	0.1936757	0.1594187	0.2330474	0.0831886
	77	87	53	24	69	39	72
PM3	-	-	-	-	-	-	-
	0.2239405	0.2675308	0.3404515	0.3419949	0.2602264	0.2928988	0.3589286
	01	2	25	61	41	57	69
PM4	-	-	-	-	-	-	-
	0.3158529	0.3659210	0.2276850	0.2838966	0.3282881	0.3200495	0.3004793
	67	22	71	46	89	27	13
PM5	-	-	-	-	-	-	-
	0.2779871	0.2588107	0.2725766	0.3531011	0.3531663	0.3251835	0.3624462
	64	87	35	27	48	48	28
PM6	-	-	-	-	-	-	-
	0.2239405	0.3258088	0.3061060	0.3271476	0.3077691	0.3153560	0.3156495
	01	27	69	72	73	7	84

Step 4: we calculate summation of P<sub>ij\*</sub>InPij

PI	AC	NV	RC	MD	RU	SLAV
-1.715506376	-1.682932279	-1.756848282	-1.668078713	-1.70305359	-1.767406786	-1.506953034

Step 5:we calculate e<sub>i</sub>

EJ 0.957442338	0.939262388	0.980515696	0.930972455	0.950492306	0.986408509	0.841046502
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Stap6: we calculate a weight for all criteria

Table 9: Calculating the entropy weight "wj"

WJ 0.102831106 0.146758904 0.04707948 0.16678968 0.11962431 0.032840811 0.384075709	Tuese se curculating and entropy weight wij							
<b>WJ</b> 0.102031100 0.140730304 0.04707340 0.10070300 0.11702431 0.032040011 0.304073703	WJ	0.102831106	0.146758904	0.04707948	0.16678968	0.11962431	0.032840811	0.384075709

From the evaluation, it has been identified that weight for each criteria



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#### **4.2 EXPREMENTAL ANALYSIS**

In this section, we compare TPSA policy and our proposed policy. In existing method, PM4 is selected which has the highest score. The existing system considers five criteria and same weight is considered. In proposed policy, we have considered seven criteria and weight used is different. Our technique chooses the best PM (in our case PM5 is considered as it has the highest score) as compared to the existing method because it has least power increase, more available capacity, least resource correlation, least migration delay.

Criteria	select PM4	select PM5			
Power increase	20	10			
Available capacity	800	400			
Number of VMs	5	7			
Resource correlation	90	50			
Migration delay	2.88	3.67			
Resource utilization		56.33			
SLA Violation		0.016789			

Table-10: Com	parison w	vith existing	g methodology

In this case, we have considered the selected PM in existing method and selected PM is proposed method

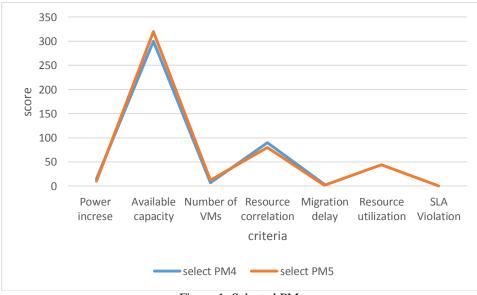


Figure 1: Selected PMs

In this case, we have considered energy consumption and compare with the existing method. This comparison shows that energy is reduced, which is shown in figure 6.



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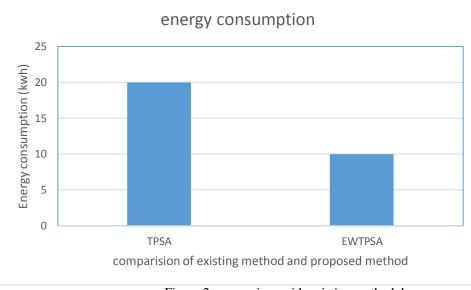


Figure 2: comparison with existing methodology

### **Conclusion:**

In our work, we have considered Different parameter used to entropy weighed method technique such as power increase, available capacity, Number of VMs, Resource correlation, Migration delay, Resource utilization, SLA violation. This paper was applied Entropy Weight method and TOPSIS power and SLA method to find the physical machine. This policy computes the scores of all the PMs that are capable of hosting a VM and selects the PM with the highest score. VM allocation based on the multicriteria is an efficient way for the optimal allocation weightage to each criteria will define the priority to that Parameter. Random weight will not justify the priority to the different parameter and entropy weighted method to generate the weightage based on the criterian considered for allocation. It focuses on minimizing the number of resources required to handle the data center workload and efficiently handle the different parameters like proper resource utilization, energy consumption, and performance of the data center.it shows experimental evaluate result depicts that out technique is performing well 20% of power increase, 20% available capacity, and improvement 20% in migration.in future work, we may use a heuristic approach to using weight.

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