Dynamic Virtual Machines Placement in a Cloud Environment by Multi-Objective Programming

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Abstract: Recently, cloud services and cloud computing have revolutionized both academic research and industrial practices. A corresponding focus on how to improve the performance of cloud computing is growing apace. It is a significant approach to allocate virtual machines (VMs) on a set of physical machines (PMs). Computing resources can be utilized effectively with the optimal distribution of the virtual machines among the physical machines. This study aims to establish the dynamic placement model of VMs by multi-objective programming (MOP) for minimizing energy consumption, maximizing effectiveness of physical machine, and minimizing the task waiting time. The genetic algorithm (GA) is used to solve the multi-objective programming models and compared with the greedy method (GM). Experiments are implemented to verify the effectiveness of the proposed methods.

Key words: Virtual machine placement, cloud computing, multi-objective programming, genetic algorithm, greedy method.

1. Introduction

Recently, cloud services and cloud computing [1]-[3] have revolutionized both academic research and industrial practices. A corresponding focus on how to improve the performance of cloud computing is growing apace. It is a significant approach to allocate virtual machines (VMs) on a set of physical machines (PMs) [4]-[7]. Computing resources can be utilized effectively with the optimal distribution of the virtual machines among the physical machines. This study aims to establish the dynamic placement model of VMs by multi-objective programming (MOP) for minimizing energy consumption, maximizing effectiveness of physical machine, and minimizing the task waiting time. Experiments are implemented to verify the effectiveness of the proposed methods.

2. Methods

Consider a set of virtual machines to be allocated in another set of physical machines (servers) in successive periods. The parameters and variables are defined in Table 1.

2.1. The multi-Objective Programming Model

Based on the static placement model in cloud computing [4], the model intends to extend the model into a dynamic one and solve the dynamic allocation problem by multi-objective programming. The model is designed as below:

$$\min Z_1 = \sum_{t=1}^l \sum_{j=1}^m P_j = \sum_{t=1}^l \sum_{j=1}^m (y_{jt} ((P_j^{\max} - P_j^{\min}) \sum_{i=1}^n (x_{ijt} R_{CPU_i}) + P_j^{\min})) \quad (1)$$

$$\min Z_2 = \sum_{t=1}^l \sum_{j=1}^m W_j = \sum_{t=1}^l \sum_{j=1}^m (y_{jt} \frac{\left| (T_{CPU_j} - \sum_{i=1}^n (x_{ijt} R_{CPU_i})) - (T_{m_j} - \sum_{i=1}^n (x_{ijt} R_{m_i})) \right|}{\sum_{i=1}^n (x_{ijt} R_{CPU_i}) + \sum_{i=1}^n (x_{ijt} R_{m_i})}) \quad (2)$$

$$\min Z_3 = \sum_{t=1}^l Time_t = \alpha \cdot \max\{y_{jt} \cdot \sum_{i=1}^n (x_{ijt} R_{CPU_i})\} \quad (3)$$

s.t.

$$\sum_{t=1}^l \sum_{j=1}^m x_{ijt} = 1, \forall i \in I \quad (4)$$

$$\sum_{t=1}^l \sum_{i=1}^n x_{ijt} R_{CPU_i} \leq y_{jt} T_{CPU_j}, \forall j \in J \quad (5)$$

$$\sum_{t=1}^l \sum_{i=1}^n x_{ijt} R_{m_i} \leq y_{jt} T_{m_j}, \forall j \in J \quad (6)$$

$$x_{ijt}, y_{jt} \in \{0, 1\} \quad \forall i \in I, \forall j \in J, \forall t \in T. \quad (7)$$

Table 1. Parameters and Variables

Notation	Description
I	The index set of virtual machines
J	The index set of physical machines
L	The index set of periods
n	The number of virtual machines
m	The number of physical machines
l	The number of periods
R_{CPU_i}	The CPU demand of each virtual machine at period t
R_{m_i}	The memory demand of each virtual machine at period t
T_{CPU_j}	The threshold of the CPU utilization with each server
T_{m_j}	The threshold of the memory utilization with each server
$P_j^{\max}$	The maximal power value the j -th server can be utilized
$P_j^{\min}$	The minimal power value when the j -th server is utilized
α	The conversion constant for waiting time and CPU utilization
x_{ijt}	The binary variable indicating if VM i is assigned to PM j at period t
y_{jt}	The binary variable indicating if PM j is in use at period t

The model minimizes the total power consumption in (1), minimizes the power wastage in (2), and minimizes the waiting time of the processes in (3). Constraint (4) assigns every virtual machine to only one physical server in every period. Inequalities (5) and (6) ensure that the usages of CPU and memory are under their capacities in the execution duration. Constraints (7) and (8) define x_{ijt}, y_{jt} as binary variables representing the association of VM i and server j in time t , and the activation of server j , respectively.

2.2. The Solution Processes

Many techniques have been proposed for solving multi-objective programming problems, and some of

them are inspired by Zimmermann's fuzzy approach [8]. This study develops the solution process based on Zimmermann's approach to solve the model as (1) - (7).

Step 1. Get the ideal solution of each objective.

To obtain the ideal solution z_i^* , each objective function is minimized independently regardless of other objectives.

Step 2. Get the anti-ideal solution of each objective.

To obtain the anti-ideal solution z_i^- , each objective function is maximized independently regardless of other objectives.

Step 3. Define the membership function of each objective by its ideal and anti-ideal solutions as below.

$$\mu_{z_i}(z_i) = \frac{z_i - z_i^-}{z_i^* - z_i^-} \quad (8)$$

The membership function evaluates the fulfillment level of each objective.

Step 4. Get the final solution.

The final solution is found by maximizing the total satisfaction level as below.

$$\begin{aligned} \lambda &= \mu_{z_1} + \mu_{z_2} + \mu_{z_3} \\ \text{s.t. } &(4) - (7) \end{aligned} \quad (9)$$

The flowchart of the solution processes is illustrated as in Fig. 1.

Fig. 1. The solution processes of MOP.

This study uses the genetic algorithm [9], [10] to carry out the computation for MOP. Genetic algorithm

(GA) is a meta-heuristic method inspired by genetic evolution for combinational optimization as described below. It is a practical approach in common use to solve complex computational problems in information and communication technology.

Algorithm-GA

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Set initial population
While (not termination condition)
    determine the fitness of each individual
    select parent population
    crossover
    mutation
End while
    
```

On the other hand, the greedy method [11], [12] is implemented for comparison.

3. Experiments and Results

Consider a set of virtual machines to be allocated in another set of physical machines (servers) in two successive periods. This study assumes identical specifications for all physical servers equipped with Pentium(R) Dual-Core E5300 / 2.6 GHz processor, 2 GB memory. Assume that every physical server can satisfy the requirements of any virtual machines. This work randomly generates 25 virtual machine samples and expresses their requirements as the utilization rate of CPU and memory in Table 2. Three scenarios of experiments are conducted using randomly selected subsets of the samples in **Case 1**: 15 VMs to 10 PMs; **Case 2**: 20 VMs to 10 PMs; and **Case 3**: 25 VMs to 7 PMs. The solutions and detailed results of the three cases are summarized in Table 3-5, and Table 6-8, respectively.

In Case 1 (Table 3), the multi-objective programming with genetic algorithm (MOP-GA) outperforms the greedy method (GM) in power wastage (Z_2) and waiting time (Z_3). In case 2 (Table 4), the MOP-GA obtains lower power consumption (Z_1) and power wastage (Z_2), but generate longer waiting time (Z_3). In case 3 (Table 5), the GM outperforms the MOP-GA except in power wastage (Z_2). However, in case 3 the computing requirements of the virtual machines exceed the resources of the physical servers, so several virtual machines are unallocated (as shown in Table 8). In Case 3, 6 virtual machines (11, 15, 19, 20, 21, 24) are unallocated with the GM, and 3 virtual machines (10, 16, 21) are unallocated with the MOP-GA. That is, the MOP-GA generates higher completion compared to the greedy method.

Table 2. Virtual Machine Samples

VM	CPU usage	Memory Usage	VM	CPU usage	Memory Usage
1	0.48	0.71	2	0.01	0.44
3	0.64	0.46	4	0.02	0.41
5	0.45	0.61	6	0.39	0.03
7	0.81	0.46	8	0.46	0.47
9	0.15	0.37	10	0.73	0.56
11	0.83	0.46	12	0.21	0.24
13	0.33	0.42	14	0.28	0.31
15	0.84	0.79	16	0.62	0.5
17	0.59	0.51	18	0.33	0.26
19	0.45	0.89	20	0.56	0.87
21	0.67	0.82	22	0.52	0.47
23	0.01	0.4	24	0.81	0.89
25	0.46	0.53			

Table 3. Solutions to Case 1 (15 VMs to 10 PMs)

By genetic algorithm	By greedy method
$Z_1=2133.39$, $Z_2=0.8971$, $Z_3=1.1$ For $t=1$ $y_{1,1}=1$, $y_{2,1}=1$, $y_{3,1}=1$, $y_{4,1}=1$, $y_{5,1}=1$, $y_{6,1}=1$, $y_{7,1}=1$, $y_{8,1}=0$, $y_{9,1}=1$, $y_{10,1}=1$, $x_{1,5,1}=1$, $x_{3,2,1}=1$, $x_{5,6,1}=1$, $x_{6,3,1}=1$, $x_{8,10,1}=1$, $x_{9,3,1}=1$, $x_{10,1,1}=1$, $x_{12,4,1}=1$, $x_{13,3,1}=1$, $x_{14,7,1}=1$, $x_{15,9,1}=1$, all remaining $x_{ij1}=0$	$Z_1=2133.39$, $Z_2=1.9539$, $Z_3=1.26$ $y_{1,1}=1$, $y_{2,1}=1$, $y_{3,1}=1$, $y_{4,1}=1$, $y_{5,1}=1$, $y_{6,1}=1$, $y_{7,1}=1$, $y_{8,1}=1$, $y_{9,1}=1$, $y_{10,1}=1$, $x_{1,7,1}=1$, $x_{2,1,1}=1$, $x_{3,6,1}=1$, $x_{4,1,1}=1$, $x_{5,5,1}=1$, $x_{6,1,1}=1$, $x_{7,8,1}=1$, $x_{8,4,1}=1$, $x_{9,2,1}=1$, $x_{10,9,1}=1$, $x_{11,10,1}=1$, $x_{12,2,1}=1$, $x_{13,3,1}=1$, $x_{14,3,1}=1$, all remaining $x_{ij1}=0$
For $t=2$ $y_{1,2}=0$, $y_{2,2}=0$, $y_{3,2}=0$, $y_{4,2}=1$, $y_{5,2}=0$, $y_{6,2}=0$, $y_{7,2}=1$, $y_{8,2}=0$, $y_{9,2}=0$, $y_{10,2}=0$, $x_{2,7,2}=1$, $x_{4,4,2}=1$, $x_{7,7,2}=1$, $x_{11,4,2}=1$, all remaining $x_{ij2}=0$	$y_{1,2}=1$, $y_{2,2}=0$, $y_{3,2}=0$, $y_{4,2}=0$, $y_{5,2}=0$, $y_{6,2}=0$, $y_{7,2}=0$, $y_{8,2}=0$, $y_{9,2}=0$, $y_{10,2}=0$ $x_{15,1,2}=1$, all remaining $x_{ij2}=0$

Table 4. Solutions to Case 2 (20 VMs to 10 PMs)

By genetic algorithm	By greedy method
$Z_1=2592.54$, $Z_2=1.3739$, $Z_3=1.61$ For $t=1$ $y_{1,1}=0$, $y_{2,1}=1$, $y_{3,1}=1$, $y_{4,1}=1$, $y_{5,1}=1$, $y_{6,1}=1$, $y_{7,1}=1$, $y_{8,1}=1$, $y_{9,1}=1$, $y_{10,1}=0$, $x_{1,6,1}=1$, $x_{2,7,1}=1$, $x_{4,9,1}=1$, $x_{5,5,1}=1$, $x_{7,7,1}=1$, $x_{8,4,1}=1$, $x_{11,9,1}=1$, $x_{12,3,1}=1$, $x_{15,8,1}=1$, $x_{17,3,1}=1$, $x_{18,5,1}=1$, $x_{19,2,1}=1$, all remaining $x_{ij1}=0$	$Z_1=2916.54$, $Z_2=2.6749$, $Z_3=1.35$ $y_{1,1}=1$, $y_{2,1}=1$, $y_{3,1}=1$, $y_{4,1}=1$, $y_{5,1}=1$, $y_{6,1}=1$, $y_{7,1}=1$, $y_{8,1}=1$, $y_{9,1}=1$, $y_{10,1}=1$, $x_{1,9,1}=1$, $x_{2,1,1}=1$, $x_{3,6,1}=1$, $x_{4,1,1}=1$, $x_{5,5,1}=1$, $x_{6,1,1}=1$, $x_{7,10,1}=1$, $x_{8,4,1}=1$, $x_{9,2,1}=1$, $x_{12,2,1}=1$, $x_{13,4,1}=1$, $x_{14,3,1}=1$, $x_{16,7,1}=1$, $x_{17,8,1}=1$, $x_{18,3,1}=1$, all remaining $x_{ij1}=0$
For $t=2$ $y_{1,2}=0$, $y_{2,2}=0$, $y_{3,2}=1$, $y_{4,2}=1$, $y_{5,2}=1$, $y_{6,2}=1$, $y_{7,2}=1$, $y_{8,2}=0$, $y_{9,2}=0$, $y_{10,2}=0$, $x_{3,7,2}=1$, $x_{6,3,2}=1$, $x_{9,7,2}=1$, $x_{10,5,2}=1$, $x_{13,3,2}=1$, $x_{14,6,2}=1$, $x_{16,6,2}=1$, $x_{20,4,2}=1$, all remaining $x_{ij2}=0$	$y_{1,2}=1$, $y_{2,2}=1$, $y_{3,2}=1$, $y_{4,2}=1$, $y_{5,2}=1$, $y_{6,2}=0$, $y_{7,2}=0$, $y_{8,2}=0$, $y_{9,2}=0$, $y_{10,2}=0$ $x_{10,1,2}=1$, $x_{11,2,2}=1$, $x_{15,5,2}=1$, $x_{19,3,2}=1$, $x_{20,4,2}=1$, all remaining $x_{ij2}=0$

Table 5. Solutions to Case 3 (25 VMs to 7 PMs)

By genetic algorithm	By greedy method
$Z_1=2778.39$, $Z_2=1.2545$, $Z_3=1.65$ For $t=1$ $y_{1,1}=1$, $y_{2,1}=1$, $y_{3,1}=1$, $y_{4,1}=1$, $y_{5,1}=1$, $y_{6,1}=1$, $y_{7,1}=1$, $x_{1,7,1}=1$, $x_{2,3,1}=1$, $x_{7,2,1}=1$, $x_{8,6,1}=1$, $x_{9,1,1}=1$, $x_{11,3,1}=1$, $x_{14,4,1}=1$, $x_{17,1,1}=1$, $x_{19,5,1}=1$, $x_{23,2,1}=1$, $x_{25,4,1}=1$, all remaining $x_{ij1}=0$	$Z_1=2664.97$, $Z_2=2.3243$, $Z_3=1.33$ $y_{1,1}=1$, $y_{2,1}=1$, $y_{3,1}=1$, $y_{4,1}=1$, $y_{5,1}=1$, $y_{6,1}=1$, $y_{7,1}=1$, $x_{2,2,1}=1$, $x_{4,1,1}=1$, $x_{5,8,1}=1$, $x_{6,1,1}=1$, $x_{7,10,1}=1$, $x_{8,5,1}=1$, $x_{9,3,1}=1$, $x_{12,2,1}=1$, $x_{13,4,1}=1$, $x_{14,3,1}=1$, $x_{17,6,1}=1$, $x_{18,4,1}=1$, $x_{23,1,1}=1$, $x_{25,7,1}=1$ all remaining $x_{ij1}=0$
For $t=2$ $y_{1,2}=1$, $y_{2,2}=1$, $y_{3,2}=1$, $y_{4,2}=1$, $y_{5,2}=1$, $y_{6,2}=1$, $y_{7,2}=1$, $x_{3,1,2}=1$, $x_{4,2,2}=1$, $x_{5,6,2}=1$, $x_{6,2,2}=1$, $x_{12,1,2}=1$, $x_{13,5,2}=1$, $x_{15,7,2}=1$, $x_{18,6,2}=1$, $x_{20,4,2}=1$, $x_{22,5,2}=1$, $x_{24,3,2}=1$, all remaining $x_{ij2}=0$	$y_{1,2}=1$, $y_{2,2}=1$, $y_{3,2}=1$, $y_{4,2}=1$, $y_{5,2}=1$, $y_{6,2}=1$, $y_{7,2}=1$, $x_{1,5,2}=1$, $x_{3,2,2}=1$, $x_{5,1,2}=1$, $x_{7,6,2}=1$, $x_{10,7,2}=1$, $x_{16,3,2}=1$, $x_{17,4,2}=1$, all remaining $x_{ij2}=0$

4. Concluding Remarks

This study establishes the dynamic placement model of VMs by multi-objective programming for

minimizing energy consumption, maximizing effectiveness of physical machine, and minimizing the task waiting time. The multi-objective programming with genetic algorithm and the greedy method are compared in solving the placement models. Three scenarios are prepared to test the feasibility and effectiveness of the model. Based on the results, the proposed MOP model is effective the virtual machine placement in cloud computing environments considering both power efficiency and allocation performance. In summary, the multi-objective programming with genetic algorithm outperforms the greedy method when the physical servers provide sufficient resources (case 1 and case 2) and higher throughput under insufficient computing resources (case 3). Without loss of generality, the two-period setting can be extended to multi-period scenarios. For future studies, various objective functions and algorithms can be consolidated to raise the precision and robustness of the models.

Table 6. Results of Case 1 (15 VMs to 10 PMs)

	VM allocated	CPU Usage	Memory Usage	VM allocated	CPU Usage	Memory Usage
	By MOP-GA			By GM		
$t=1$						
PM1	10	0.73	0.56	2, 4, 6	0.42	0.88
PM2	3	0.64	0.46	9, 12	0.36	0.61
PM3	6, 9, 13	0.87	0.82	13, 14	0.61	0.73
PM4	12	0.21	0.24	8	0.46	0.47
PM5	1	0.48	0.71	5	0.45	0.61
PM6	5	0.45	0.61	3	0.64	0.46
PM7	14	0.28	0.31	1	0.48	0.71
PM8	-	0	0	7	0.81	0.46
PM9	15	0.84	0.79	10	0.73	0.56
PM10	8	0.46	0.47	11	0.83	0.46
$t=2$						
PM1	-	0	0	15	0.84	0.79
PM2	-	0	0	-	0	0
PM3	-	0	0	-	0	0
PM4	4, 11	0.85	0.87	-	0	0
PM5	-	0	0	-	0	0
PM6	-	0	0	-	0	0
PM7	2, 7	0.82	0.9	-	0	0
PM8	-	0	0	-	0	0
PM9	-	0	0	-	0	0
PM10	-	0	0	-	0	0

Table 7. Results of Case 2 (20 VMs to 10 PMs)

	VM allocated	CPU Usage	Memory Usage	VM allocated	CPU Usage	Memory Usage
	By MOP-GA			By GM		
$t=1$						
PM1	-	0	0	2, 4, 6	0.42	0.88
PM2	19	0.45	0.89	9, 12	0.36	0.61
PM3	12, 17	0.8	0.75	14, 18	0.61	0.57
PM4	8	0.46	0.47	8, 13	0.79	0.89
PM5	5, 18	0.78	0.87	5	0.45	0.61
PM6	1	0.48	0.71	3	0.64	0.46
PM7	2, 7	0.82	0.9	16	0.62	0.5
PM8	15	0.84	0.79	17	0.59	0.51
PM9	4, 11	0.85	0.87	1	0.48	0.71
PM10	-	0	0	7	0.81	0.46
$t=2$						
PM1	-	0	0	10	0.73	0.56
PM2	-	0	0	11	0.83	0.46
PM3	6, 13	0.72	0.45	19	0.45	0.89
PM4	20	0.56	0.87	20	0.56	0.87
PM5	10	0.73	0.56	15	0.84	0.79
PM6	14, 16	0.9	0.81	-	0	0
PM7	3, 9	0.79	0.83	-	0	0
PM8	-	0	0	-	0	0
PM9	-	0	0	-	0	0
PM10	-	0	0	-	0	0

Table 8. Results of Case 3 (25 VMs to 7 PMs)

	VM allocated	CPU Usage	Memory Usage	VM allocated	CPU Usage	Memory Usage
	By MOP-GA			By GM		
$t=1$						
PM1	9,17	0.74	0.88	4, 6, 23	0.42	0.88
PM2	7,23	0.82	0.86	2, 12	0.36	0.61
PM3	2,11	0.84	0.9	9, 14	0.61	0.57
PM4	14,25	0.74	0.84	13, 18	0.79	0.89
PM5	19	0.45	0.89	8	0.45	0.61
PM6	8	0.46	0.47	17	0.64	0.46
PM7	1	0.48	0.71	25	0.62	0.5
$t=2$						
PM1	3,12	0.85	0.7	5	0.59	0.51
PM2	4,6	0.41	0.44	3	0.48	0.71
PM3	24	0.81	0.89	16	0.81	0.46
PM4	20	0.56	0.87	17	0.73	0.56
PM5	13,22	0.85	0.89	1	0.83	0.46
PM6	5,18	0.78	0.87	7	0.45	0.89
PM7	15	0.84	0.79	10	0.56	0.87
Unallocated		10,16,21			11, 15, 19, 20, 21, 24	

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