A NSGA-II-based Approach for Web Service Resource Allocation On Cloud

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***Abstract*—Web service and Cloud computing have significantly reformed the software industry. The need for web service allocation in the cloud environment is increasing dramatically. In order to reduce the cost for service providers as well as improve the utilization of cloud resource for cloud provider, this paper formulates the web service resource allocation in cloud environment problem as a two-level of multi-objective bin packing problem. It proposes a NSGA-II-based algorithm with specific design genetic operators to solve it. The results are compared with two variances of the algorithm. The results show the proposed algorithm can provide reasonably good results with low violation rate.**

I. Introduction

Service Oriented Architecture (SOA) and Cloud computing have significantly reformed the software industry. SOA provides a decentralized application architecture which allows software composition and reuse in a large, global scale. Meanwhile, Cloud computing provides a scalable, reliable, and flexible infrastructure to web services.

As the dramatically increasing of web services and cloud facilities, the management of resources has become a critical issue. In recent years, as the power bill has become the largest fraction of the operating cost of Cloud facility [1], to reduce power consumption has become a paramount concern for Cloud service providers. In order to achieve that, a common approach is to re-allocate jobs and web services to a minimum number of physical machines (PMs) [2]. Therefore, idle computing servers are turned down or put into save mode. This optimization process, often called *consolidation* involves with two levels of delivery mode, Software as a service (SaaS) and Infrastructure as a service (IaaS). Because of the complexity, consolidation tasks for IaaS and SaaS are often considered as separated tasks with different objectives. For SaaS, the challenges concentrated on satisfying the Service Level Agreements (SLAs) with unpredictable requests and minimizing cost. Whereas, for IaaS, the challenges are the scheduling of VMs on PMs and energy conservation.

There are extensive algorithms proposed for each delivery mode, [3] proposes two algorithms for energy efficient scheduling of VMs in Cloud, an exact VM allocation algorithm which is an extended Bin-Packing approach, and a migration algorithm which is based on an integer linear programming. [4] proposes a heuristic algorithm for service consolidation in a set of servers with minimizing costs while avoiding the overloading of servers and satisfying end-to-end response time constraints.

However, as the two level of resource allocation are interact to each other, we believe the resource allocation task for IaaS and SaaS cannot be separated. They should be considered as one global optimization with multi-objectives from the perspectives of both service providers and cloud providers. Therefore, in this paper, we first propose a model for solving *web service resource allocation on Cloud (WSRAC)*. Secondly, we propose a NSGA-II-based multi-objective algorithm with specifically designed operators to solve the problem. The two objectives are:

1) Propose a model for solving IaaS and SaaS resource allocation together
2) Propose a NSGA-II-based algorithm to solve the problem.

The rest of the paper is organized as follows. Section II discusses the traditional approaches for IaaS and SaaS and the power model for VM allocation. It will also introduce the related work of evolutionary multi-objective optimization techniques. Section III describes the definition of the WSRAC problem. Section IV introduces the representation and genetic operators for WSRAC problem. Section V illustrates the experiment design, results and discussions. Section VI draw a conclusion and discuss the future work.

II. Background

A. Traditional approaches

[5] proposed a single-objective genetic algorithm to solve the placement of web service (SaaS) in physical machines. Their major contributions are three-fold. Firstly, they consider web services as a workflow and optimize the makespan of a workflow. Second, they designed a representation to solve the problem. Third, they considered the storage node and compute service separate deployment.

[6] developed a *Resource-Allocation-Throughput (RAT)* model for web service allocation. *RAT model* mainly defines several important variables for an atomic service which represents a software component. Based on this model, they noticed that, firstly, throughput equals coming rate if the resources of the VM are not exhausted. Secondly, increasing coming rate will also increases throughput until the allocated resource is exhausted. Thirdly, when the resource is exhausted, the

throughput will not increase as request increasing. At this time, the virtual machine reaches its capacity.

Anton Beloglazov [7] proposed two algorithms for VM allocation, the first one is a bin-packing algorithm, called Modified Best Fit decreasing (MBFD) which is used when new VM allocation request arrives. The second algorithm, named Minimization of Migration, is used to adjust the current VMs allocation according to the CPU utilization of a physical machine. Their experiments have shown that these methods lead to a substantial reduction of energy consumption in Cloud data centers.

B. Power Model

Shekhar's research [8] is one of the earliest in energy aware consolidation for cloud computing. They conducted experiments of independent applications running in physical machines. Their observation was CPU utilization and disk utilization are the key factors affecting the energy consumption. They also explained that only consolidating services into the minimum number of physical machines does not necessary achieve energy saving, because the service performance degradation leads to longer execution time, which increases the energy consumption.

Bohra and et.al [9] developed an energy model to profile the power of a VM. They monitored the sub-components of a VM include: CPU, cache, disk, and DRAM and purpose a linear model Eq.1. Total power consumption is a linear combination of the power consumption of CPU, cache and DRAM and disk. The parameter α and β are determined based on the observations of machine running CPU or IO intensive jobs.

$$P_{(total)} = \alpha P_{\{CPU,cache\}} + \beta P_{\{DRAM,disk\}} \tag{1}$$

Although this model can achieve an average of 93% of accuracy, it is hard to employ in solving WSRAC problem.

Anton Beloglazov [7] proposed a comprehensive energy model for energy-aware resource allocation problem (Eq.2. P_{max} is the maximum power consumed when a virtual machine is fully utilized; k is the fraction of power consumed by the idle server (i.e. 70%); and u is the CPU utilization. This linear relationship between power consumption and CPU utilization is also observed by [10], [11]. We also adopt this power model in our work.

$$P(u) = k \cdot P_{max} + (1-k) \cdot P_{max} \cdot u \tag{2}$$

C. Evolutionary Multi-objective Optimization

A multi-objective optimization problem consists of multiple objective functions to be optimized. We consider all the objective functions are to be minimized. Therefore, a multi-objective optimization problem can be stated as follows:

$$\min \quad \vec{f}(\vec{x}) = (f_1(\vec{x}), \ldots, f_m(\vec{x})), \tag{3}$$

$$s.t. \quad \vec{x} \in \Omega. \tag{4}$$

where Ω stands for the feasible region of $\vec{x}$.

Evolutionary Multi-objective Optimization Algorithm (EMOA) are ideal for solving multi-objective optimization problems [12], because EMOAs work with a population of solutions. With an emphasis on moving towards the true Pareto-optimal region, a EMOA algorithm can be used to find multiple Pareto-optimal solutions in one single simulation run [13]. Therefore, this project would employ EMOA approaches. This is also the first time employ EMOAs technique on WSRAC problem.

III. Problem Description

We consider the WSRAC problem as a multi-objective problem with two potentially conflicting objectives, minimizing the overall cost of web services and minimizing the overall energy consumption of the used physical machines.

To solve the WSRAC problem we model an atomic service as request and its coming rate, also known as frequency. The request is modeled as two critical resources: CPU time $A = \{A_1, A_2, \ldots, A_t\}$ and memory consumption $M = \{M_1, M_2, \ldots, M_t\}$, for each request consumes a A_t amount of CPU time and M_t amount of memory. The coming rate of an atomic is denoted as $R = \{R_1, R_2, \ldots, R_t\}$. In real world scenario, the size and the number of a request are both variant which are unpredictable, therefore, this is one of the major challenges in Cloud resource allocation. In this paper, we use fixed coming rate information extracted from a real world dataset to represent real world service requests.

The Cloud data center has a number of available physical machines which are modeled as CPU time $PA = \{PA_1, PA_2, \ldots, PA_p\}$ and memory $PM = \{PM_1, PM_2, \ldots, PM_p\}$. PA_p denotes the CPU capacity of a physical machine and PM_p denotes the size of memory. A physical machine can be partitioned or virtualized into a set of virtual machines; each virtual machine has its CPU time $VA = \{VA_1, VA_2, \ldots, VA_v\}$ and memory $VM = \{VM_1, VM_2, \ldots, VM_v\}$. In this work, we consider homogeneous physical machine which means physical machines have the same size of CPU time and memory. The utilization of a CPU of a virtual machine is denoted as $U = \{U_1, U_2, \ldots, U_v\}$. The utilization can be calculated according to Eq.5. We define $i \prec v$ as the service i is allocated on VM v.

$$U_v = \begin{cases} \frac{\sum_{i=1}^{t} R_i \cdot A_i}{VA_v}, i \prec v, \text{If } \sum_{i=1}^{t} R_i \cdot A_i < 1 \\ 1 \qquad\qquad\qquad\qquad\quad \text{, otherwise} \end{cases} \tag{5}$$

The cost of a type of virtual machine is denoted as $C = \{C_1, C_2, \ldots, C_v\}$.

In order to satisfied the performance of an end user, Service providers often define Service Level Agreements (SLAs) to ensure the service quality. In this work, we define throughput as a SLA measurement [14]. Throughput denotes the number of requests that a service could successfully process in a period of time. According to *RAT* model, the throughput equals to the number of requests when the allocated resource is sufficient. Therefore, if a VM reaches its utilization limitation, it means services have been allocated exceedingly. Therefore, all services in that VM suffered from performance degradation.

Then we define two objective functions as the total energy consumption and the total cost of virtual machines:

minimize

$$Energy = \sum_{i=1}^{p}(k \cdot V_{max} + (1-k)V_{max} \cdot \sum_{j=1}^{v} U_j), \tag{6}$$

$$Cost = \sum_{j=1} C_j \tag{7}$$

subject to

$$\begin{aligned} \sum_{n=1}^{t} M_n \cdot R_n < VM_j, n \prec j \\ \sum_{j=1}^{v} VM_j < PM_i, j \prec i \\ \sum_{j=1}^{v} VA_j < PA_i, j \prec i \end{aligned} \tag{8}$$

It is easy to notice that there is no decision variable in both objective functions. This is because the decision variable is the number of the virtual machine and the allocation of web service which cannot be represented as decision variables.

IV. Methods

A. Chromosome Representation

As the WSAP is a two level of bin-packing problem, the first level is that bins represent physical machines and items represent virtual machines, the second level is bins represent virtual machines and items represent web services. Therefore, we design the representation in two hierarchies, virtual machine level and physical machine level.

Figure 1 shows an example individual which contains seven service allocations. Each allocation of a service is represented as a pair where the index of each pair represents the number of web service. The first number indicates the type of virtual machine that the service is allocated in. The second number denotes the number of virtual machine. For example, in Figure 1, service #1 and service #2 are both allocated in the virtual machine #1 while service #1 and service #5 are allocated in the different virtual machines which share the same type. The first hierarchy shows the virtual machine in which a service is allocated by defining VM type and number. Noticed that, the VM type and number are correlated once they are initialized. With this feature, the search procedure is narrowed down in the range of existing VMs which is largely shrinking the search space. The second hierarchy shows the relationship between a physical machine and its virtual machines, which are implicit. The physical machine is dynamically decided according to the virtual machines allocated on it. That is, we employ a simple heuristic method, the boundary of a physical machine is calculated by adding up the virtual machines resources sequentially until a physical machine is full. The reason we designed this heuristic is because a physical machine is always fully used before launching another. Therefore, VM consolidation is inherently achieved.

Clearly, specifically designed operators are needed to manipulate chromosomes. Therefore, based on this representation, we further developed initialization, mutation, constraint handling and selection method.

B. Initialization

Algorithm 1 Initialization

Inputs:
VM CPU Time VA and memory VM,
Service CPU Time A and memory M
consolidation factor c
Outputs: A population

```
for Each service t do
    Find its most suitable VM Type
    Randomly generate a VM type vmType which is equal or better than its most suitable type
    if There are existing VMs with vmType then
        randomly generate a number u
        if u < consolidation factor then
            randomly choose one existing VM with vmType to allocate
        else
            launch a new VM with vmType
        end if
    else
        Create a new VM with its most suitable VM type
    end if
end for
```

The initialization Alg.1 is designed based on domain knowledge with a certain level of randomness in order to reduce the search space as well as generate a diverse population. With the service resource requirement data and VM capacity information, we are able to find the most suitable type of VM for a service. The most suitable type of VM is a VM just capable of running the service. However, launching a new VM for the service does not necessary improve the overall performance, for other existing, stronger VMs may still capable of running the service. Therefore, we introduce a three-stage of random allocation method. Firstly, it randomly generates a type which ensures the capacity of the VM. Secondly, we design a consolidation factor c that controls the allocation of service in existing VMs. The consolidation factor is a real number manually selected from 0 to 1. If a random number is smaller than the factor, then, select a existing VM with equal probability. Otherwise, launch a new VM.

C. Mutation

The design principle for mutation operator is that it enables individual to explore the entire feasible search space. Therefore, a good mutation operator has two significant features, first is the exploration ability and the other is its ability to keep an individual within the feasible regions. In order to achieve these two goals, firstly, we generate a random virtual machine type which has greater or equal capacity than the service needs. It ensures the feasible solution as well as exploration. Then, we consider whether a service is consolidated with a predefined probability c. The consolidation is conducted with a roulette wheel method which assigns fitness values to each

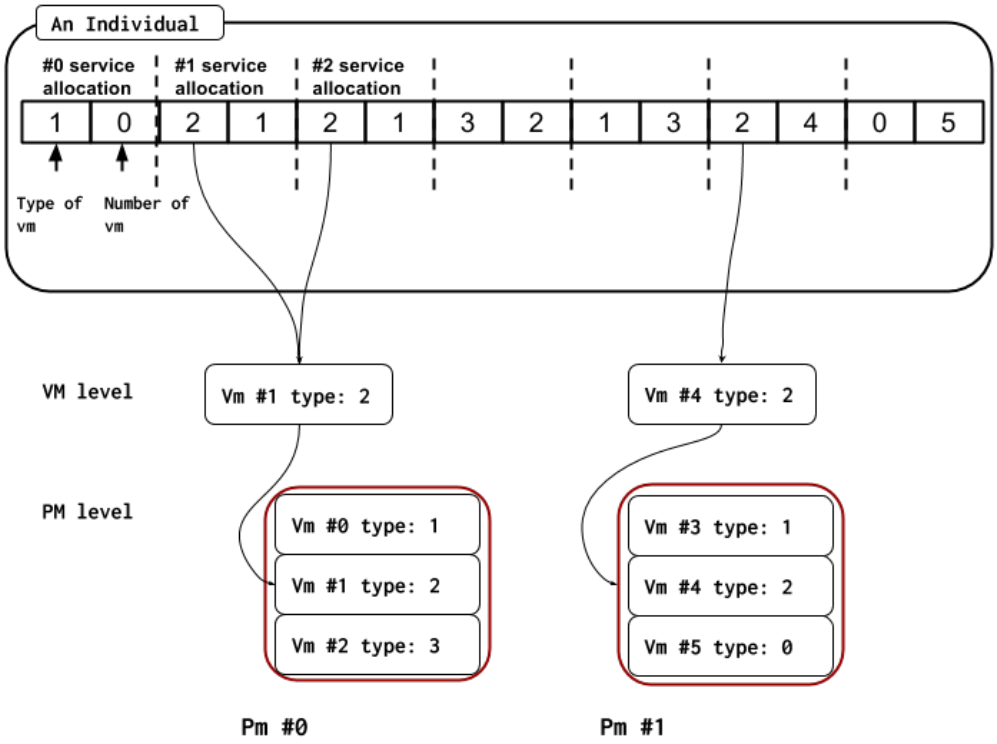


Fig. 1. An example chromosome representation

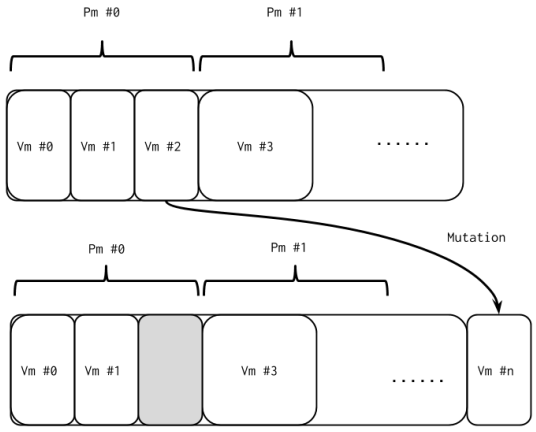


Fig. 2. A big VM could lead to low-utility of PMs

VM according to the reciprocal of its current utilization. The higher the utilization, the lower the fitness value it is assigned. Therefore, a lower utilization VM has a greater probability to be chosen. At last, if a new VM is launched, it will not be placed at the end of VM lists. Instead, it will be placed at a random position among the VMs. The reason is illustrated in Figure 2. In the example, VM #2 is mutated into a new type and be placed at the end of the VM list. However, because of the size of VM #3 is too large for PM #0, it causes a low-utility of PMs. This problem can be solved with the random insertion method.

Algorithm 2 Mutation

Inputs:
An individual VM CPU Time VA and memory VM,
Service CPU Time A and memory M
consolidation factor c
Outputs: A mutate individual

```
for Each service num do
    Randomly generate a number u
    if u < mutation rate then
        find the most suitable VM Type for this service
        Randomly generate a number k
        if k < consolidation factor then
            calculate the utilization of used VMs
            assign each VM with a fitness value of 1 / utilization and
            generate a roulette wheel according to their fitness values
            Randomly generate a number p, select the VM according to p
            Allocate the service
        else
            launch a new VM with the most suitable VM Type
            insert the new VM in a randomly choose position
        end if
    end if
end for
```

D. Constraint Violation

The original NSGA-II algorithm introduced a violation number. In our problem, the number violation is the sum of services which that are allocated in the degraded VMs. If there are excessive services allocated in a VM, then all the services are suffered from a degradation in performance. The

violation number is used in the selection procedure, where the individuals with less violations are always preferred.

E. Selection

Our design uses the binary tournament selection with a constrained-domination principle. A constrained-domination principle is defined as following. A solution I is considered constraint-dominate a solution J if any of the following condition is true:

1) Solution I is feasible, solution is not,
2) Both solutions are infeasible, I has smaller overall violations,
3) Both solutions are feasible, solution I dominates solution J.

As we introduced the constraint violation in the previous section, an individual with no or less violation is always selected. This method has been proved effective in the original NSGA-II paper.

F. Fitness Function

The cost fitness (Eq.7) is determined by the type of VMs at which web service are allocated. The energy fitness is according to Eq.6, the utilizations (Eq.5) of VM are firstly converted into the utilizations of PM according to the proportion of VMs and PMs CPU capacity.

G. Algorithm

The main difference between our approach and the original NSGA-II is our approach has no crossover operator. It is because the random switch of chromosome would complete destroy the order of VMs. Therefore, we only apply mutation as the exploration method. Then, the algorithm becomes a parallel optimization without much iteration between its offspring,which is often addressed as Evolutionary Strategy [15].

V. Experiment

A. Dataset and Problem Design

This project is based on both real-world datasets *WS-Dream* [16] and simulated datasets [17]. The *WS-Dream* includes a network latency matrix between 339 user centers and 5825 candidate locations. In this project, we mainly use the service frequency (request coming rate) information. In this work, we only consider the rental of virtual machines with fixed fees (monthly rent). For VM configuration II, the CPU time and memory were selected manually and cost were selected proportional to their CPU capacity. The maximum PM's CPU and memory are set to 3000 and 8000 respectively. The energy consumption is set to 220W according to [17].

We designed six problems shown in Table I, listed with increasing size and difficulty, which are used as representative samples of the WSRAC problem.

We conducted two comparison experiments. For the first experiment, we are going to compare NSGA-II with violation control with without violation control. In second experiment, two mutation operators are compared. First is the roulette wheel mutation, second is mutation with greedy algorithm. The mutation with greedy algorithm is a variant of roulette wheel mutation. The only difference is that instead of select consolidate VM with fitness values, it will always select the VM with lowest utilization. Therefore, there is a greedy method embedded in the mutation.

Algorithm 3 NSGA-II for WSRP

Inputs:
VM CPU Time VA and memory VM,
PM CPU Time PA and memory PM,
Service CPU Time A and memory M
consolidation factor c
Outputs: A Non-dominated Set of solutions

```
Initialize a population P
while Termination Condition is not meet do
    for Each individual do
        Evaluate the fitness values
        Calculate the violation
    end for
    non-Dominated Sorting of P
    calculate crowding distance
    while child number is less than population size do
        Selection
        Mutation
        add the child in a new population U
    end while
    Combine P and U { for elitism}
    Evaluate the combined P and U
    Non-dominated sorting and crowding distance for combined population
    Include the top popSize ranking individuals to the next generation
end while
```

TABLE I
Problem Settings

Problem	1	2	3	4	5	6
Number of service	20	40	60	80	100	200

The experiments were conducted on a personal laptop with 2.3GHz CPU and 4.0 GB RAM. For each approach, 30 independent runs are performed for each problem with constant population size 100. The maximum number of iteration is 200. k equals 0.7. We set mutation rate and consolidation factor to 0.9 and 0.01.

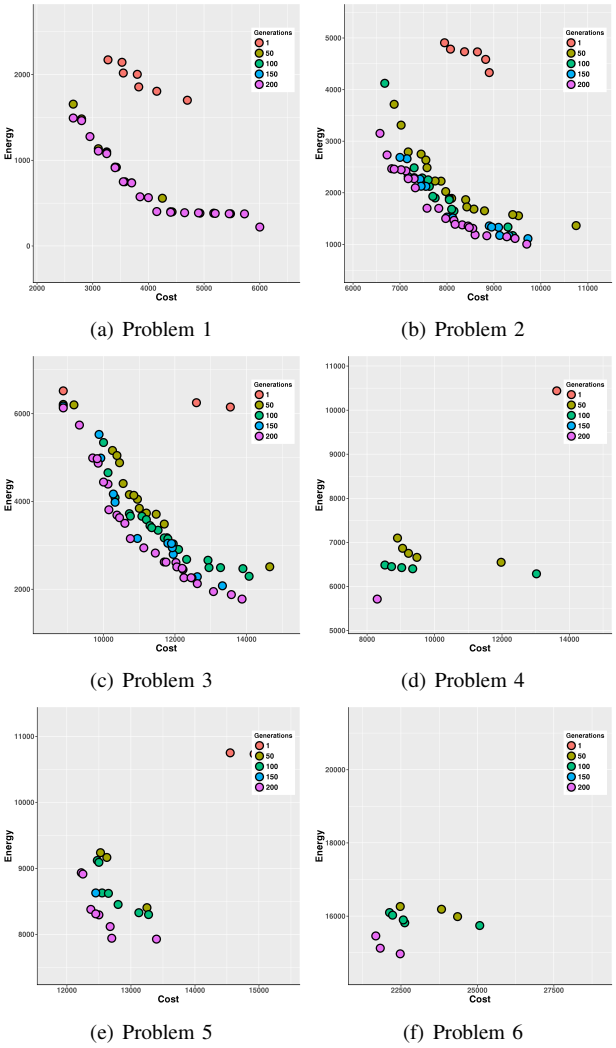
B. Results

Selection Method with violation Control vs. without violation control

As we conducted the experiment for 30 runs, we first obtain an average non-dominated set over 30 runs by collecting the results from a specific generation from all 30 runs, and then apply a non-dominated sorting over it.

TABLE II
VM configurations

VM Type	CPU Time	Memory	Cost
1	250	500	25
2	500	1000	50
3	1500	2500	150
4	3000	4000	300



(a) Problem 1 (b) Problem 2

(c) Problem 3 (d) Problem 4

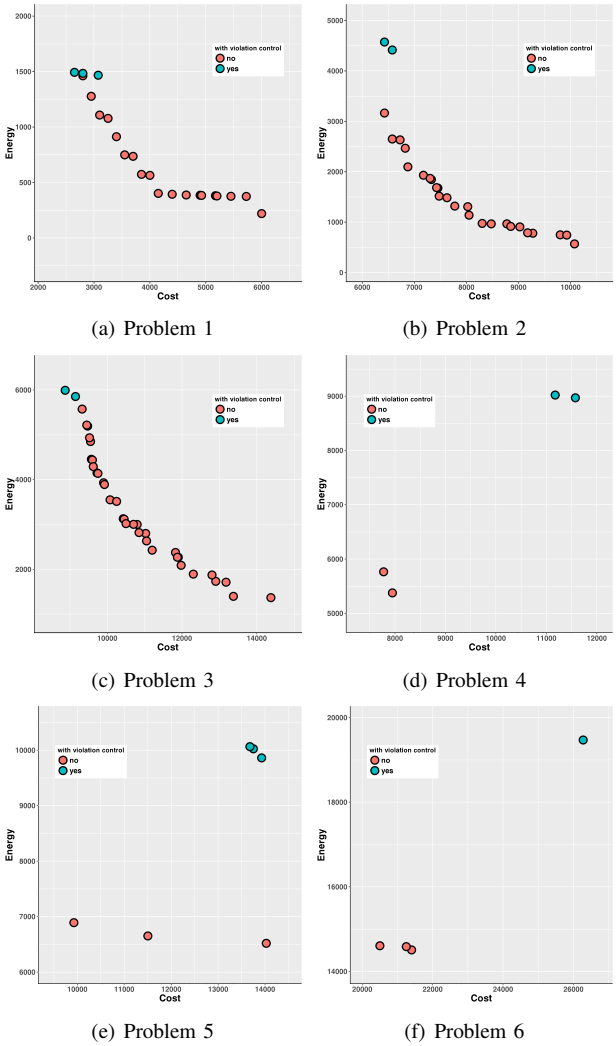
(e) Problem 5 (f) Problem 6

Fig. 3. Non-dominated solutions evolve along with the generation

Firstly, we show the non-dominated solutions evolve along with the evolution process in Figure 3. These results come from selection method without violation control. As it illustrated, different color represents different generations from the first to 200th. For problem 1, because the problem size is small, the algorithm converged before it before 100th generations. Therefore, the non-dominated set from 100th and 150th are overlapping with results from 200th. For problem 2 and problem 3, they show the improvement of fitness values clearly. For problem 4 onwards, the algorithm can only obtain a few solutions as the problem size is large, it is difficult to find solutions.

Then, the non-dominated sets of the last generation from two selection methods are compared in Figure 4. There are much fewer results are obtained from the violation control method throughout all cases. For the first three problems, the non-dominated set from the violation control method has similar quality as the no violation control method. However, from problem 4 onwards, the results are much worse in terms of fitness values. This is because the method without violation control is stuck in the infeasible regions and provide high-violation rate solutions. From figure 5, we compare the violation percentage between method with and without violation control. It is clear that, the violation percentages from violation control method are lower than 10%. It proves violation control has a great ability to prevent the individual from searching the infeasible region. On the other hand, without violation control, although, the algorithm can provide much more solutions, most of them have a high violation rate over 10% which are trivial solutions.

The mutation rate is set to 0.9 and c is 0.01, because the feasible region is very narrow and scattered. Therefore, in order to avoid stuck in the local optima. The mutation rate has to be set large. For the factor c, a larger percentage would easily lead the algorithm stuck in the infeasible regions.



(a) Problem 1 (b) Problem 2

(c) Problem 3 (d) Problem 4

(e) Problem 5 (f) Problem 6

Fig. 4. non-dominated solutions comparison between selection with violation control and without violation control

Mutation with roulette wheel vs. Mutation with greedy algorithm

Table III shows the fitness value comparison between muta-

TABLE III
COMPARISON BETWEEN TWO MUTATION METHODS

Problem	roulette wheel mutation		Greedy mutation	
	cost fitness	energy fitness	cost fitness	energy fitness
1	2664.6 ± 66.4	1652.42 ± 18.2	2661.7 ± 56.9	1653.2 ± 18.2
2	6501.1 ± 130.2	4614.0 ± 110.7	6495.37 ± 110.7	4132.5 ± 80.4
3	8939.2 ± 118.5	6140.7 ± 204.0	9020.5 ± 204.0	5739.6 ± 148.6
4	11633.7 ± 301.1	9301.9 ± 254.0	12900.6 ± 243.0	9376.3 ± 120.9
5	14102.0 ± 231.7	10164.8 ± 238.9	14789.2 ± 238.8	9876.3 ± 120.9
6	27194.3 ± 243.0	19914.4 ± 307.5	27654.2 ± 307.5	19187.1 ± 176.6

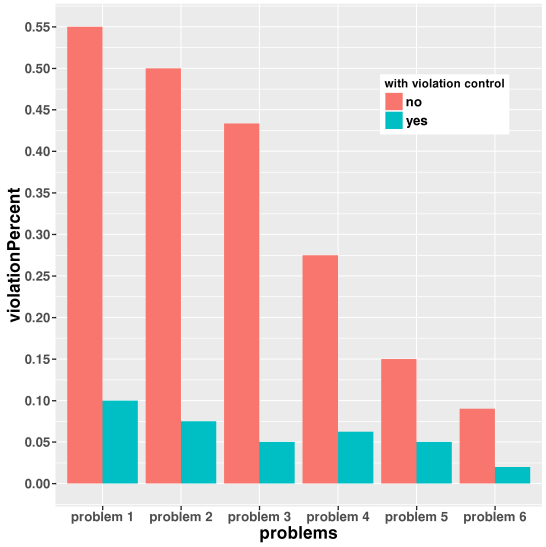


Fig. 5. Violation Percentage comparison between selection with violation control and without violation control

tion methods. According to statistics significant test, there is little difference between methods. The possible reason is the consolidation factor is set to 0.01. In each mutation iteration, there is only 1% probability that a service will be consolidated in an existed VM, therefore, the influence between different consolidation strategies can be neglected.

VI. CONCLUSION

In this paper, we first propose a multi-objective formulation of a two levels of bin packing problem, web service resource allocation on Cloud. It solves the resource allocation in IaaS and SaaS at the same time. Two objectives, minimizing the cost from service providers' perspective and minimizing the energy consumption from cloud provider's objective are achieved. Secondly, we propose a NSGA-II based algorithm with specific designed genetic operators to solve the problem. The results are compared with different variances of the algorithm. The results show our approach can solve the very complicate optimization problem.

With current work as a baseline, in future work, we could improve the quality of solutions as well as provide better violation control mechanisms.

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