Multi-objective dynamic virtual machine consolidation in the cloud using ant colony system

2 authors:

Adnan Ashraf
Åbo Akademi University
44 PUBLICATIONS **829** CITATIONS

SEE PROFILE

Ivan Porres
Åbo Akademi University
177 PUBLICATIONS **2,721** CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Project   MegaM@Rt2 (ECSEL) View project

Project   MegaM@Rt2 View project

Multi-objective dynamic virtual machine consolidation in the cloud using ant colony system

Adnan Ashraf* and Ivan Porres

Faculty of Natural Sciences and Technology, Åbo Akademi University, Finland

In this paper, we present a novel multi-objective ant colony system algorithm for virtual machine (VM) consolidation in cloud data centers. The proposed algorithm builds VM migration plans, which are then used to minimize over-provisioning of physical machines (PMs) by consolidating VMs on under-utilized PMs. It optimizes two objectives that are ordered by their importance. The first and foremost objective in the proposed algorithm is to maximize the number of released PMs. Moreover, since VM migration is a resource-intensive operation, it also tries to minimize the number of VM migrations. The proposed algorithm is empirically evaluated in a series of experiments. The experimental results show that the proposed algorithm provides an efficient solution for VM consolidation in cloud data centers. Moreover, it outperforms two existing ant colony optimization based VM consolidation algorithms in terms of number of released PMs and number of VM migrations.

Keywords: virtual machines; consolidation; metaheuristic; ant colony system; cloud computing

1. Introduction

Cloud data centers comprise thousands of physical machines (PMs) and networking devices. These resources and their cooling infrastructure incur huge energy footprints. High energy consumption not only translates into a high operating cost, but also leads to huge carbon emissions [1, 2]. Therefore, energy footprint of data centers is a major concern for cloud providers. The high energy consumption of data centers can partly be attributed to the large-scale installations of computing and cooling infrastructures, but more importantly it is due to the inefficient use of the computing resources [3].

Hardware virtualization technologies allow to share a PM among multiple, performance-isolated virtual machines (VMs) to improve resource utilization. Further improvement in resource utilization and reduction in energy consumption can be achieved by consolidating VMs on PMs and switching idle PMs off or to a low-power mode. VM consolidation has emerged as one of the most effective and promising techniques to reduce energy footprint of cloud data centers [3, 4]. A VM consolidation approach uses live VM migration to consolidate VMs on a reduced set of PMs. Thereby, allowing some of the underutilized PMs to be turned-off or switched to a low-power mode to conserve energy.

There is currently an increasing amount of interest on developing and evaluating efficient VM consolidation approaches for cloud data centers. Over the past few years, researchers have used a multitude of ways to develop novel VM consolidation approaches [3, 5–15]. Some of these approaches have also been reported in recent literature reviews [16, 17].

The main output of a VM consolidation algorithm is a VM migration plan, which is implemented by first migrating VMs from one PM to another and then shutting down or allocating new work to the idle PMs. The quality of a VM consolidation algorithm can be evaluated according to different criteria, including the number of released PMs (to be maximized), the number of VM migrations from one PM to

---

*Corresponding author. Email: adnan.ashraf@abo.fi

another (to be minimized), and the algorithm execution time (to be minimized). Moreover, since a migration plan with a higher number of released PMs is always preferred to a migration plan with a lower number of VM migrations, maximizing the number of released PMs takes precedence over minimizing the number of VM migrations.

The VM consolidation problem is an NP-hard combinatorial optimization problem [18]. Therefore, it requires advanced strategies in order to be viable in practice. One way to address this problem is to use the exact optimization techniques, such as mixed-integer linear programming, which find optimal solutions with exponential runtime complexity. However, such techniques are mostly impractical for realistic, large-sized problem instances. Moreover, the currently available commercial, exact optimization tools, such as IBM ILOG CPLEX[1], do not provide support for multi-objective optimization problems. A widely-used alternative approach to solve difficult combinatorial optimization problems involves the use of metaheuristics [19]. Metaheuristics are high-level procedures that efficiently explore the search-space of available solutions with the aim to find near-optimal solutions with a polynomial time complexity [20].

Some of the recent works [4, 18, 21, 22] on VM consolidation use a highly adaptive metaheuristic called ant colony optimization (ACO) [23]. The existing ACO-based VM consolidation approaches [4, 18, 21, 22] tend to use single-objective, single-colony algorithms with an aggregate objective function (AOF) that tries to combine multiple objectives. The benefit of the AOF approach is that it reduces complexity and may improve the runtime of the algorithm by limiting the search to a subspace of the feasible solutions. However, the main drawback is that a correct combination of the objectives requires certain weights to be assigned to each objective, which often requires an in-depth knowledge of the problem domain [17]. Therefore, the assignment of the weights is essentially subjective [24]. Moreover, an AOF may not combine the optimization objectives in an appropriate manner. For instance, the AOFs in the existing ACO-based VM consolidation approaches [4, 18, 21, 22] do not allow to order the objectives by their importance.

In this paper, we present a novel multi-objective ACO-based VM consolidation algorithm for cloud data centers that, according to our evaluation, outperforms the existing ACO-based VM consolidation algorithms [4, 18, 21, 22]. It uses ant colony system (ACS) [25], which is currently one of the best performing ACO algorithms. The proposed multi-objective ACS algorithm for VM consolidation is called MOACS and it optimizes two objectives. The first and foremost objective in MOACS is to maximize the number of released PMs. Moreover, since VM migration is a resource-intensive operation, MOACS also tries to minimize the number of VM migrations. We adapt and use a multi-objective, multi-colony ACS algorithm by Gambardella et al. [26], which orders the objectives by their importance. The proposed algorithm is not dependent on a particular deployment architecture or system topology. Therefore, it can be implemented in centralized as well as decentralized deployment architectures and system topologies, as the one proposed in [21].

1.1 Contributions

The main task of the proposed MOACS algorithm is to find a VM migration plan that maximizes the number of released PMs while minimizing the number of VM

---

migrations. In the rest of this section, we summarize the main contributions of this paper.

Improved Multi-Objective, Multi-Colony Optimization

MOACS advances the state of the art on ACO-based VM consolidation by implementing a multi-objective, multi-colony ACS algorithm. It extends our previous single-objective, single-colony ACO algorithm for VM consolidation [4, 18] and similar works by other researchers [21, 22] that implement single-objective, single-colony ACO algorithms. The proposed multi-objective, multi-colony approach eliminates the need for an AOF and allows to combine the optimization objectives in an appropriate manner.

Improved Reduction of Search Space

Since VM consolidation is an NP-hard problem, it requires fast and scalable algorithms. In order to improve the runtime performance of the proposed algorithm, we present three simple constraints in Section 3. These constraints determine which PMs and VM migrations can be excluded from the consolidation process without compromising on the quality of the solutions. We refine two constraints from our previous work [4, 18] and complement them with a new constraint concerning neighborhoods of PMs.

Improved Experimental Results

We have implemented the proposed MOACS algorithm in Java and have compared it with two existing ACO-based VM consolidation algorithms. The first one is the single-objective, single-colony max-min ant system VM consolidation algorithm by Feller et al. [21], that we name Feller-ACO for evaluation. We selected the Feller-ACO algorithm for comparison due to its excellent overall performance in many aspects as shown by its authors [21]. The second one is our previously published single-objective, single-colony ACS VM consolidation algorithm [4], that we refer to as ACS for evaluation. The ACS algorithm was selected as baseline for our work since it outperformed many other existing algorithms at the time of publication, as shown in [4]. Our results show that the proposed MOACS algorithm outperforms Feller-ACO in all attributes: number of released PMs, number of VM migrations, packing efficiency, and algorithm execution time. Similarly, it outperforms ACS [4] in all attributes except in execution time.

We proceed as follows. Section 2 provides background and discusses important related works. The proposed MOACS algorithm is described in detail in Section 3 while its experimental evaluation is presented in Section 4. Finally, we present our conclusions in Section 5.

2. Background and Related Work

Ant colony optimization (ACO) metaheuristic is inspired from the foraging behavior of real ant colonies [23]. While transporting food from the food source to their nest, ants deposit and follow trails of a chemical substance on their paths called pheromone. It allows them to indirectly communicate with one another to find better paths between their nest and the food source. Empirical results from previous research on ACO has shown that the simple pheromone trail following behavior of ants can give rise to the emergence of the shortest paths.

Each ant finds a complete path or solution, but high quality solutions emerge from the indirect communication and global cooperation among multiple concurrent ants [4]. Ants must also avoid stagnation, which is a premature convergence to

a suboptimal solution. It is achieved by using pheromone evaporation and stochastic state transitions. There are a number of ACO algorithms, such as ant system (AS), ant colony system (ACS), and max-min ant system (MMAS) [23]. ACS [25] is currently one of the best performing ant algorithms. Therefore, in this paper, we apply ACS to the VM consolidation problem.

The existing ACO-based resource allocation, VM placement, and VM consolidation approaches include [4, 18, 21, 22, 27–30]. Yin and Wang [28] applied ACO to the nonlinear resource allocation problem, which seeks to find an optimal allocation of a limited amount of resources to a number of tasks. Chaharsooghi and Kermani [29] proposed a modified version of ACO for the multi-objective resource allocation problem. Feller et al. [21] applied the single-objective, single-colony MMAS algorithm to the VM consolidation problem in the context of cloud computing. Ferdaus et al. [22] integrated ACS with a vector algebra-based server resource utilization capturing technique [31]. In our previous work [27], we applied the original single-objective, single-colony ACS algorithm [25] to the web application consolidation problem. Similarly, in our previous work [4, 18], we used the original ACS algorithm [25] for energy-aware VM consolidation in cloud data centers.

Gao et al. [30] used a multi-objective ACS algorithm with two equally important objectives: minimize energy consumption and minimize resource wastage. In their approach, both energy consumption and resource wastage are derived from the number of PMs used for the placement of VMs. Their approach only provides an initial placement of VMs on PMs. It does not migrate VMs from one PM to another. Therefore, it can not be used to consolidate VMs or to minimize the number of VM migrations. The output of Gao et al.'s algorithm is a Pareto set of solutions, from which a solution is randomly selected. A drawback of this approach is that the objectives can not be ordered by their importance. Moreover, the randomly selected solution may not be the most desired solution. To the best of our knowledge, none of the existing ACO-based VM consolidation approaches use a multi-objective ACS algorithm that orders the objectives by their importance.

The main difference between the existing ACO-based VM consolidation approaches [4, 18, 21, 22] and our proposed MOACS algorithm is that the existing approaches tend to use a single-objective, single-colony ACO algorithm with an AOF that tries to combine multiple objectives, whereas MOACS uses a multi-objective ACS algorithm with two independent ant colonies. The first colony maximizes the number of released PMs, while the second colony minimizes the number of VM migrations. We adapt and use a multi-objective, multi-colony ACS algorithm by Gambardella et al. [26], which was originally proposed for the vehicle routing problem with time windows.

3. Multi-Objective ACS Algorithm for VM Consolidation

In this section, we present our proposed multi-objective ACS-based VM consolidation algorithm (MOACS). As its first objective, MOACS maximizes the number of released PMs $|P_R|$. Moreover, its second objective is to minimize the number of VM migrations nM. Since a global best migration plan Ψ^+ with a higher number of released PMs $|P_R|$ is always preferred to a Ψ^+ with a lower $|P_R|$ even if the number of VM migrations nM is higher in the former Ψ^+, maximizing $|P_R|$ takes precedence over minimizing nM. For the sake of clarity, important concepts and notations used in the following sections are tabulated in Table 1.

Figure 1 illustrates MOACS architecture. MOACS coordinates the operations of two ACS-based ant colonies, which simultaneously optimize their respective objec-

Table 1.: Summary of concepts and their notations

M	set of migration plans
P	set of PMs
P_R	set of PMs that are released when a migration plan Ψ is enforced
T	set of tuples
T_k	set of tuples not yet traversed by ant k
V	set of VMs
V_p	set of VMs running on a PM p
$C_{p_{de}}$	total capacity vector of the destination PM p_{de}
N	a neighborhood of PMs
p_{de}	destination PM in a tuple
p_{so}	source PM in a tuple
q	a uniformly distributed random variable
S	a random variable selected according to (7)
Scr_k	thus far best score of ant k
$U_{p_{de}}$	used capacity vector of the destination PM p_{de}
$U_{p_{so}}$	used capacity vector of the source PM p_{so}
U_v	used capacity vector of the VM v
η	heuristic value
τ	amount of pheromone
τ_0	initial pheromone level
Ψ	a migration plan
Ψ^+	the global best migration plan
Ψ^+_{nM}	thus far best migration plan from ACS_{nM}
Ψ^+_{PR}	thus far best migration plan from $\text{ACS}_{|PR|}$
Ψ_k	ant-specific migration plan of ant k
Ψ^m_k	ant-specific temporary migration plan of ant k
$\Delta^{nM}_{\tau_s}$	additional pheromone amount given to the tuples in Ψ^+_{nM}
$\Delta^{PR}_{\tau_s}$	additional pheromone amount given to the tuples in Ψ^+_{PR}
α	pheromone decay parameter in the global updating rule
β	parameter to determine the relative importance of η
ρ	pheromone decay parameter in the local updating rule
q_0	parameter to determine relative importance of exploitation
nA	number of ants that concurrently build their migration plans
nI	number of ant generations
nM	number of VM migrations
$f(\Psi)$	objective function in (3) concerning number of released PMs
$g(\Psi)$	objective function in (13) concerning number of VM migrations

tives. The first objective concerning the number of released PMs $|P_R|$ is optimized by the first colony called $\text{ACS}_{|PR|}$. Similarly, the second colony called ACS_{nM} optimizes the second objective concerning the number of VM migrations nM. Both colonies work independently and use independent pheromone and heuristic matrices. However, they collaborate on the global best migration plan Ψ^+, which is maintained by MOACS.

In the VM consolidation problem, each PM $p \in P$ hosts multiple VMs $v \in V$. Each PM that hosts at least one VM is a potential *source PM*. Both the source PM and the VM are characterized by their resource utilizations, such as CPU utilization and memory utilization. MOACS uses a notion of neighborhoods of
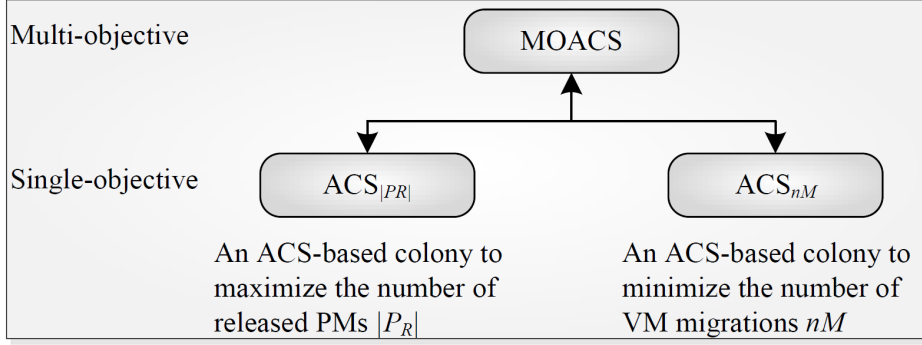
Figure 1.: MOACS architecture

PMs. Neighborhoods are mutually exclusive subsets of P. A neighborhood is an abstract entity that represents a set of closely-located PMs in a cloud data center. For example, the PMs in a data center rack may constitute a neighborhood of PMs. A VM can be migrated to any other PM located in any neighborhood N. Therefore, every other PM within as well as outside the neighborhood of the source PM is a potential *destination PM*, which is also characterized by its resource utilizations. Thus, MOACS makes a set of tuples T, where each tuple $t \in T$ consists of three elements: source PM p_{so}, VM v, and destination PM p_{de}

$$t := (p_{so}, v, p_{de}) \tag{1}$$

The computation time of the proposed VM consolidation algorithm is primarily based on the number of tuples $|T|$. Therefore, in order to reduce the computation time, MOACS applies three constraints, which result in a reduced set of tuples by removing some least important and unwanted tuples. The first constraint ensures that only under-utilized PMs are used as the source PMs. Similarly, the second constraint allows only under-utilized PMs to be considered as the destination PMs. In other words, migrations from and to well-utilized PMs are excluded. The rationale is that a well-utilized PM should not become part of the consolidation process because migrating to a well-utilized PM may result in its overloading. Similarly, migrating from a well-utilized PM is less likely to result in the termination of the source PM and thus it would not reduce the total number of required PMs. The third constraint further restricts the size of the set of tuples $|T|$ by preventing inter-neighborhood migrations. Therefore, as a general rule, a VM can only be migrated to another PM within the neighborhood of its source PM. The only exception to this rule is when a neighborhood has only one PM in it. In this case, the VMs from the lone PM can be migrated to any other PM in any neighborhood. By applying these three simple constraints in a series of preliminary experiments, we observed that the computation time of the algorithm was significantly reduced without compromising on the quality of the solutions.

The space complexity of the proposed algorithm is $\mathcal{O}(|T|)$, where $|T|$ is the number of tuples. Moreover, the worst-case space complexity corresponds to a VM consolidation scenario that does not involve any well-utilized PMs. In such a scenario, each PM is considered as a source as well as a destination PM. The maximum number of tuples in the worst-case is computed as

$$maximum \ |T| := |P| \cdot |V| \cdot (|N| - 1) \tag{2}$$

where $|P|$ is the number of PMs, $|V|$ is the number of VMs, and $|N|$ is the neighborhood size. Since real VM consolidation scenarios usually involve one or more

well-utilized PMs and the proposed algorithm excludes migrations from and to well-utilized PMs, the actual number of tuples $|T|$ in a real scenario is often smaller than that of the worst-case scenario.

The pseudocode of the proposed MOACS algorithm is presented in Algorithm 1. Initially, the global best migration plan Ψ^+ is not known. Therefore, Ψ^+ is empty (line 2). The main loop in line 1 iterates until a stopping criterion is met. For instance, when all remaining PMs are well-utilized or when no further improvements are achieved in a given number of consecutive iterations [26]. In each iteration of the main loop, the two ACS-based colonies $\text{ACS}_{|PR|}$ and ACS_{nM} try to find the global best migration plan Ψ^+ according to their respective objectives. $\text{ACS}_{|PR|}$ tries to find a migration plan with a higher number of released PMs $|P_R|$ (line 3). Similarly, ACS_{nM} tries to find a migration plan with fewer VM migrations (line 4). The global best migration plan Ψ^+ is updated every time an improved migration plan is found. If $\text{ACS}_{|PR|}$ finds a migration plan with a higher number of released PMs (line 5), Ψ^+ is updated according to the thus far best migration plan from $\text{ACS}_{|PR|}$ denoted as Ψ^+_{PR} (line 6). Likewise, when ACS_{nM} finds a migration plan with fewer VM migrations, but with at least as many released PMs P_R as in Ψ^+ (lines 8–9), Ψ^+ is updated according to the thus far best migration plan from ACS_{nM} denoted as Ψ^+_{nM} (line 10). Finally, at the end of each iteration of the main loop, VMs are consolidated according to the global best migration plan Ψ^+ and the released PMs are terminated (line 13).

3.1   ACS-based Colony to Maximize the Number of Released PMs

The $\text{ACS}_{|PR|}$ colony optimizes the first objective concerning the number of released PMs $|P_R|$. Therefore, the objective function for the $\text{ACS}_{|PR|}$ algorithm is

$$maximize\ f(\Psi) := |P_R| \tag{3}$$

where Ψ is the migration plan and P_R is the set of PMs that will be released when Ψ is enforced. Since the primary objective of VM consolidation is to minimize the number of active PMs, the objective function is defined in terms of number of released PMs $|P_R|$. Moreover, when a migration plan is enforced, we apply a constraint which reduces the number of VM migrations nM by restricting migrations

---

Algorithm 1 Multi-objective ACS algorithm for VM consolidation (MOACS)

1: **while** until a stopping criterion is met **do**
2:     $\Psi^+ := \emptyset$
3:     $\Psi^+_{PR} := ACS_{|PR|}$
4:     $\Psi^+_{nM} := ACS_{nM}$
5:     **if** $\Psi^+ = \emptyset \vee f(\Psi^+_{PR}) > f(\Psi^+)$ **then**
6:         $\Psi^+ := \Psi^+_{PR}$
7:     **end if**
8:     **if** $f(\Psi^+_{nM}) \geq f(\Psi^+)$ **then**
9:         **if** $g(\Psi^+_{nM}) > g(\Psi^+)$ **then**
10:             $\Psi^+ := \Psi^+_{nM}$
11:         **end if**
12:     **end if**
13:     consolidate VMs according to Ψ^+ and terminate released PMs
14: **end while**

---

to only those PMs that are not included in the set of released PMs P_R, that is

$$\forall \, p_{de} \, \in \, P \mid p_{de} \, \notin \, P_R \qquad (4)$$

In our approach, a PM can only be considered as released when all VMs migrate from it. Therefore, the set of released PMs P_R is defined as

$$P_R := \{\forall p \, \in \, P | V_p = \emptyset\} \qquad (5)$$

where V_p is the set of VMs running on a PM p. Thus, a PM can only be included in the set of released PMs P_R when it no longer hosts any VMs.

Since there is no notion of path in the VM consolidation problem, ants deposit pheromone on the tuples defined in (1). Each of the nA ants uses a stochastic state transition rule to choose the next tuple to traverse. The state transition rule in $\mathrm{ACS}_{|PR|}$ is called pseudo-random-proportional-rule [25]. According to this rule, an ant k chooses a tuple s to traverse next by applying

$$s := \begin{cases} \arg \max_{u \, \in \, T_k} \{[\tau_u] \cdot [\eta_u]^\beta\}, & \text{if } q \leq q_0 \\ S, & \text{otherwise} \end{cases} \qquad (6)$$

where τ denotes the amount of pheromone and η represents the heuristic value associated with a particular tuple. β is a parameter to determine the relative importance of the heuristic value with respect to the pheromone value. The expression *arg max* returns the tuple for which $[\tau] \cdot [\eta]^\beta$ attains its maximum value. $T_k \subset T$ is the set of tuples that remain to be traversed by ant k. $q \in [0,1]$ is a uniformly distributed random variable and $q_0 \in [0,1]$ is a parameter. S is a random variable selected according to the probability distribution given in (7), where the probability $prob_s$ of an ant k to choose tuple s to traverse next is defined as

$$prob_s := \begin{cases} \frac{[\tau_s] \cdot [\eta_s]^\beta}{\sum\limits_{u \, \in \, T_k} [\tau_u] \cdot [\eta_u]^\beta}, & \text{if } s \, \in \, T_k \\ 0, & \text{otherwise} \end{cases} \qquad (7)$$

The heuristic value η_s of a tuple s is defined as

$$\eta_s := \begin{cases} \frac{U_{p_{de}} + U_v}{C_{p_{de}}}, & \text{if } U_{p_{de}} + U_v \leq C_{p_{de}} \\ 0, & \text{otherwise} \end{cases} \qquad (8)$$

where $C_{p_{de}}$ is the total capacity vector of the destination PM p_{de}, $U_{p_{de}}$ is the used capacity vector of p_{de}, and likewise U_v is the used capacity vector of the VM v in tuple s. The heuristic value η is based on the ratio of $(U_{p_{de}} + U_v)$ to $C_{p_{de}}$. Therefore, destination PMs with the minimum unused capacity receive the highest amount of heuristic value. Thus, the heuristic value favors VM migrations that would result in a reduced under-utilization of PMs. Moreover, the constraint $U_{p_{de}} + U_v \leq C_{p_{de}}$ prevents VM migrations that would result in the overloading of the destination PM p_{de}. In the proposed algorithm, we assumed two resource dimensions, which represent CPU utilization and memory utilization. However, if necessary, it is possible to add more dimensions in the total and used capacity vectors.

The stochastic state transition rule in (6) and (7) prefers tuples with a higher pheromone concentration and which result in a higher number of released PMs. The first case in (6) where $q \leq q_0$ is called exploitation [25]. It chooses the best

tuple that attains the maximum value of $[\tau] \cdot [\eta]^\beta$. The second case, called biased exploration, selects a tuple according to (7). The exploitation helps the ants to quickly converge to a high quality solution, while at the same time, the biased exploration helps them to avoid stagnation by allowing a wider exploration of the search space. In addition to the stochastic state transition rule, $\text{ACS}_{|PR|}$ also uses a global and a local pheromone trail evaporation rule. The global pheromone trail evaporation rule is applied towards the end of an iteration after all ants complete their migration plans. It is defined as

$$\tau_s := (1 - \alpha) \cdot \tau_s + \alpha \cdot \Delta_{\tau_s}^{PR} \tag{9}$$

where $\alpha \in (0, 1]$ is the pheromone decay parameter and $\Delta_{\tau_s}^{PR}$ is the additional pheromone amount that is given only to those tuples that belong to the thus far best migration plan from $\text{ACS}_{|PR|}$ denoted as Ψ_{PR}^+ in order to reward them. It is defined as

$$\Delta_{\tau_s}^{PR} := \begin{cases} |P_R|, & \text{if } s \in \Psi_{PR}^+ \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

The local pheromone trail update rule is applied on a tuple when an ant traverses the tuple while making its migration plan. It is defined as

$$\tau_s := (1 - \rho) \cdot \tau_s + \rho \cdot \tau_0 \tag{11}$$

where $\rho \in (0, 1]$ is similar to α and τ_0 is the initial pheromone level, which is computed as the multiplicative inverse of the product of the number of PMs $|P|$ and the approximate optimal $|\Psi|$

$$\tau_0 := (|\Psi| \cdot |P|)^{-1} \tag{12}$$

Here, any very rough approximation of the optimal $|\Psi|$ suffices [25]. The pseudo-random-proportional-rule in $\text{ACS}_{|PR|}$ and the global pheromone trail update rule are intended to make the search more directed. The pseudo-random-proportional-rule prefers tuples with a higher pheromone level and a higher heuristic value. Therefore, the ants try to search other high quality solutions in the close proximity of the thus far global best solution. On the other hand, the local pheromone trail update rule complements exploration of other high quality solutions that may exist far form the thus far global best solution. This is because whenever an ant traverses a tuple and applies the local pheromone trail update rule, the tuple looses some of its pheromone and thus becomes less attractive for other ants. Therefore, it helps in avoiding stagnation where all ants end up finding the same solution or where they prematurely converge to a suboptimal solution.

The pseudocode of the $\text{ACS}_{|PR|}$ algorithm is given as Algorithm 2. The algorithm makes a set of tuples T using (1) and sets the pheromone value of each tuple to the initial pheromone level τ_0 by using (12) (line 2). Then, it iterates over nI iterations (line 3), where each iteration $i \in nI$ creates a new generation of nA ants that concurrently build their migration plans (lines 4–20). Each ant $k \in nA$ iterates over $|T|$ tuples (lines 6–18). It computes the probability of choosing the next tuple to traverse by using (7) (line 7). Afterwards, based on the computed probabilities and the stochastic state transition rule in (6) and (7), each ant chooses a tuple t to traverse (line 8) and adds t to its temporary migration plan Ψ_k^m (line 9). The local pheromone trail update rule in (11) and (12) is applied on t (line 10). If the

Algorithm 2 ACS-based colony to maximize the number of released PMs ($\text{ACS}_{|PR|}$)

1:    $\Psi_{PR}^{+} := \emptyset$, $M := \emptyset$
2:    $\forall t \in T | \tau_t := \tau_0$
3:    **for** $i \in [1, nI]$ **do**
4:      **for** $k \in [1, nA]$ **do**
5:        $\Psi_k^m := \emptyset, \Psi_k := \emptyset, Scr_k := 0$
6:        **while** $|\Psi_k^m| < |T|$ **do**
7:          compute $prob_s \quad \forall s \in T$ by using (7)
8:          choose a tuple $t \in T$ to traverse by using (6)
9:          $\Psi_k^m := \Psi_k^m \cup \{t\}$
10:         apply local update rule in (11) on t
11:         **if** the migration in t does not overload destination PM p_{de} **then**
12:           update used capacity vectors $U_{p_{so}}$ and $U_{p_{de}}$ in t
13:           **if** $f(\Psi_k^m) > Scr_k$ **then**
14:             $Scr_k := f(\Psi_k^m)$
15:             $\Psi_k := \Psi_k \cup \{t\}$
16:           **end if**
17:          **end if**
18:        **end while**
19:        $M := M \cup \{\Psi_k\}$
20:      **end for**
21:      $\Psi_{PR}^{+} := \arg\max_{\Psi_k \in M} \{f(\Psi_k)\}$
22:      apply global update rule in (9) on all $s \in T$
23:    **end for**
24: return Ψ_{PR}^{+}

---

migration in t does not overload the destination PM p_{de}, the used capacity vectors at the source PM $U_{p_{so}}$ and the destination PM $U_{p_{de}}$ in t are updated to reflect the impact of the migration (line 12). Then, the objective function in (3) is applied on Ψ_k^m. If it yields a score higher than the ant's thus far best score Scr_k (line 13), t is added to the ant-specific migration plan Ψ_k (line 15). Afterwards, when all ants complete their migration plans, all ant-specific migration plans are added to the set of migration plans M (line 19), each migration plan $\Psi_k \in M$ is evaluated by applying the objective function in (3), the thus far global best VM migration plan Ψ^{+} is selected (line 21), and the global pheromone trail update rule in (9) and (10) is applied on all tuples (line 22). Finally, when all iterations $i \in nI$ complete, $\text{ACS}_{|PR|}$ returns the thus far best migration plan from $\text{ACS}_{|PR|}$ denoted as Ψ_{PR}^{+} (line 24).

The time complexity of the $\text{ACS}_{|PR|}$ algorithm is $\mathcal{O}(nI \cdot |T|^2)$, where nI is the number of ant generations and $|T|$ is the number of tuples. It can be derived from the pseudocode in Algorithm 2. The main loop in line 3 iterates over nI. The second loop in line 4 does not add to the time complexity because the ants concurrently build their migration plans. The while loop in line 6 iterates over $|T|$. Finally, the probability calculation in line 7 requires an iteration over $|T|$.

3.2   *ACS-based Colony to Minimize the Number of VM Migrations*

The ACS_{nM} algorithm tries to find a migration plan with fewer VM migrations, but with at least as many released PMs P_R as in Ψ^{+}. Thus, the objective function

for ACS_{nM} is

$$maximize\ g(\Psi) := (nM)^{-1} \tag{13}$$

where Ψ is the migration plan and nM is the number of VM migrations. Since VM migration is a resource-intensive operation, the objective function for ACS_{nM} is defined as the multiplicative inverse of the number of VM migrations nM.

The ants in the ACS_{nM} colony use the same pseudo-random-proportional-rule as in (6) and (7) to choose the next tuple to traverse. Moreover, as a general rule, the heuristic value η_s in (8) favors tuples with a greater VM used capacity vector U_v. Therefore, the VM migrations that are more likely to result in a reduced number of VM migrations receive a higher amount of heuristic value η_s. Thus, the heuristic value η_s in (8) supports the objective function of ACS_{nM} in (13).

The ACS_{nM} colony also uses the same local pheromone trail update rule as in (11). However, the global pheromone trail evaporation rule in ACS_{nM} is defined as

$$\tau_s := (1 - \alpha) \cdot \tau_s + \alpha \cdot \Delta_{\tau_s}^{nM} \tag{14}$$

where $\Delta_{\tau_s}^{nM}$ is the additional pheromone amount that is given only to those tuples that belong to the thus far best migration plan from ACS_{nM} denoted as Ψ_{nM}^{+} in order to reward them. It is defined as

$$\Delta_{\tau_s}^{nM} := \begin{cases} (nM)^{-1}, & \text{if } s \in \Psi_{nM}^{+} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

The pseudocode of the ACS_{nM} algorithm is given as Algorithm 3. Most of the steps in ACS_{nM} are similar to those in the $\text{ACS}_{|PR|}$ colony in Algorithm 2 (lines 1–12). Similarly, in line 13, the algorithm uses the objective function concerning the number of released PMs $|P_R|$ defined in (3) instead of the objective function concerning the number of VM migrations nM defined in (13) because at this step it is important to find a migration plan with a higher number of released PMs $|P_R|$. However, when selecting the thus far best migration plan from ACS_{nM} denoted as Ψ_{nM}^{+} (line 21), all ant-specific migration plans $\Psi_k \in M$ are evaluated first by applying the objective function concerning the number of released PMs $|P_R|$ defined in (3) and then by the objective function concerning the number of VM migrations nM defined in (13). Therefore, the migration plan with the highest number of released PMs $|P_R|$ and a lower number of VM migrations nM is selected as the best migration plan Ψ_{nM}^{+}. Afterwards, the algorithm applies the global pheromone trail update rule of the ACS_{nM} colony defined in (14) and (15) on all tuples (line 22). Finally, it returns Ψ_{nM}^{+} (line 24).

The time complexity of the ACS_{nM} algorithm is similar to that of the $\text{ACS}_{|PR|}$ algorithm. Since the $\text{ACS}_{|PR|}$ and ACS_{nM} colonies work concurrently and independently, the overall time complexity of the proposed MOACS algorithm for finding the global best migration plan Ψ^{+} is $\mathcal{O}(nI \cdot |T|^2)$.

4. Evaluation

In this section, we describe the experimental evaluation of the proposed MOACS algorithm and its comparison with the single-objective, single-colony MMAS VM

Algorithm 3 ACS-based colony to minimize the number of VM migrations (ACS_{nM})

1: $\Psi_{nM}^{+} := \emptyset,\ M := \emptyset$
2: $\forall t \in T | \tau_t := \tau_0$
3: **for** $i \in [1, nI]$ **do**
4:　**for** $k \in [1, nA]$ **do**
5:　　$\Psi_k^m := \emptyset, \Psi_k := \emptyset, Scr_k := 0$
6:　　**while** $|\Psi_k^m| < |T|$ **do**
7:　　　compute $prob_s\ \ \forall s \in T$ by using (7)
8:　　　choose a tuple $t \in T$ to traverse by using (6)
9:　　　$\Psi_k^m := \Psi_k^m \cup \{t\}$
10:　　　apply local update rule in (11) on t
11:　　　**if** the migration in t does not overload destination PM p_{de} **then**
12:　　　　update used capacity vectors $U_{p_{so}}$ and $U_{p_{de}}$ in t
13:　　　　**if** $f(\Psi_k^m) > Scr_k$ **then**
14:　　　　　$Scr_k := f(\Psi_k^m)$
15:　　　　　$\Psi_k := \Psi_k \cup \{t\}$
16:　　　　**end if**
17:　　　**end if**
18:　　**end while**
19:　　$M := M \cup \{\Psi_k\}$
20:　**end for**
21:　$\Psi_{nM}^{+} := \arg \max_{\Psi_k \in M}\{f(\Psi_k)\} \wedge\ \arg \max_{\Psi_k \in M}\{g(\Psi_k)\}$
22:　apply global update rule in (14) on all $s \in T$
23: **end for**
24: return Ψ_{nM}^{+}

---

consolidation algorithm (Feller-ACO) by Feller et al. [21] and our previously published single-objective, single-colony ACS VM consolidation algorithm (ACS) [4].

We have implemented our proposed MOACS algorithm as a Java program called the MOACS Solver. It is available online under an open-source license[1]. We have also developed Java solvers for the Feller-ACO [21] and ACS [4] algorithms.

4.1 Experimental Design

The objective of the experiment was to compare the performance of the three implemented solvers: ACS, MOACS, and Feller-ACO. The input of these algorithms is a VM consolidation problem that can be characterized by the following parameters: number of PMs, number of VMs to consolidate, CPU utilization of each VM, memory requirements of each VM, and the current location of each VM. We used a factorial experiment design [32], in which the three solvers were tested in four different scenarios: (1) low CPU and small memory requirements with respect to the capacity of the PMs, (2) high CPU and large memory requirements, (3) high CPU and small memory requirements, and (4) low CPU and large memory requirements. The experiment used randomly generated workloads, homogeneous VMs, and homogeneous PMs. The experimental parameters are summarized in Table 2 and Table 3. For Scenario 1, the number of VMs to consolidate was 1000 and the number of PMs was 100 (ratio 10:1), while in the other 3 scenarios there were 1000 VMs and 200 PMs (ratio 5:1). The neighborhood size was set to 5 and the neigh-

---

[1] https://github.com/SELAB-AA/moacs-wac

Table 2.: Experiment design

Algorithm	CPU Utilization	
ACS, MOACS, Feller-ACO	Low	High
Small	Scenario 1 $\|V\|=1000$ $\|P\|=100$ $\|N\|=5$ Number of runs=10	Scenario 3 $\|V\|=1000$ $\|P\|=200$ $\|N\|=5$ Number of runs=10
Memory		
Large	Scenario 4 $\|V\|=1000$ $\|P\|=200$ $\|N\|=5$ Number of runs=10	Scenario 2 $\|V\|=1000$ $\|P\|=200$ $\|N\|=5$ Number of runs=10

Table 3.: ACO parameters

α	β	ρ	q_0	nA	nI
0.1	2.0	0.1	0.9	10	2

bors were chosen randomly. The ACO parameters used in the ACS, MOACS, and Feller-ACO solvers are tabulated in Table 3. These parameter values were obtained in a series of preliminary experiments. The dependent variables of the experiment were:

- Number of released PMs after consolidation, to be maximized.
- Packing efficiency, defined as the ratio between the number of released PMs and the total number of PMs, to be maximized.
- Number of VM migrations during consolidation, to be minimized.
- Solver execution time, to be minimized.

4.2 Execution

The three solvers under evaluation used approximated algorithms. Therefore, we ran each solver ten times for each scenario, every time with a different random seed. Consequently, the experiment comprised a total of 40 test runs for each solver. The experiments were run on an Intel Core i7-4790 processor with 16 gigabytes of memory.

4.3 Results

4.3.1 Number of Released PMs and Packing Efficiency

Figure 2 presents the number of released PMs by the ACS, MOACS, and Feller-ACO solvers for the different scenarios as box plots. Moreover, Table 4 provides a summary of the results in the numerical form. The table also provides the packing efficiency achieved by each solver. This variable is derived easily from the number of released PMs.

The results show that the MOACS solver was able to release 25% to 37% more

(a) S1: Low CPU, small memory

(b) S3: High CPU, small memory

(c) S4: Low CPU, large memory
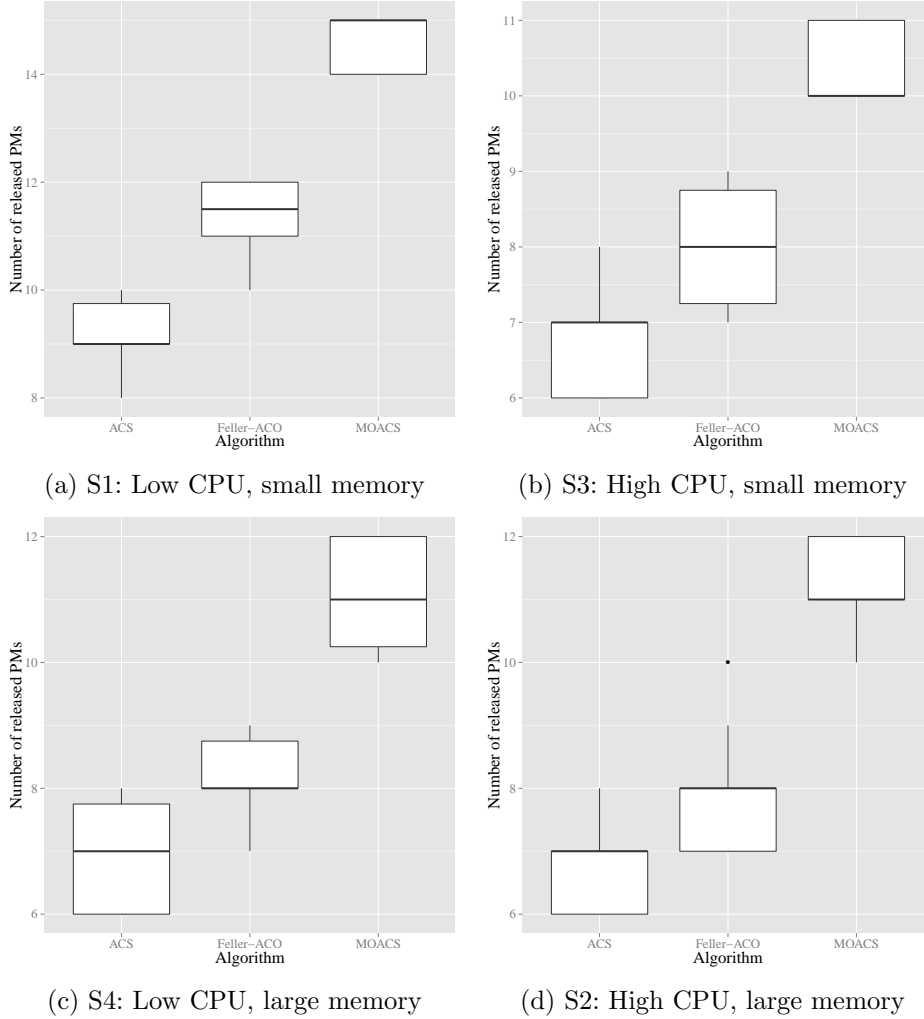
(d) S2: High CPU, large memory

Figure 2.: Number of released PMs

PMs than the Feller-ACO solver, depending on the scenario. For example, in Scenario 1, MOACS released 15 PMs (median of 10 test runs) while Feller-ACO released only 11 PMs (median of 10 test runs). Since the packing efficiency is derived from the number of released PMs, it follows a similar trend. The difference in the number of released PMs between the MOACS and Feller-ACO solvers is statistically significant (Wilcoxon Signed-Rank Test, p-value = 0.005).

4.3.2   *Number of VM Migrations*

The third dependent variable of interest in our experiment was the number of VM migrations, which should be minimized. Figure 3 presents the results for this variable for the three solvers in the graphical form while Table 5 provides a summary of the results in the numerical form.

Again, we can observe that MOACS outperforms Feller-ACO for this objective. The results show that the MOACS solver was required to perform only 82% to 83% of the number of migrations required by the Feller-ACO solver to achieve an even better packing efficiency. For example, in Scenario 1, MOACS required 189 migrations (median of 10 test runs) while Feller-ACO required 226 migrations (median of 10 test runs). The difference in the number of migrations per solver is statistically significant (Wilcoxon Signed-Rank Test, p-value = 0.006).
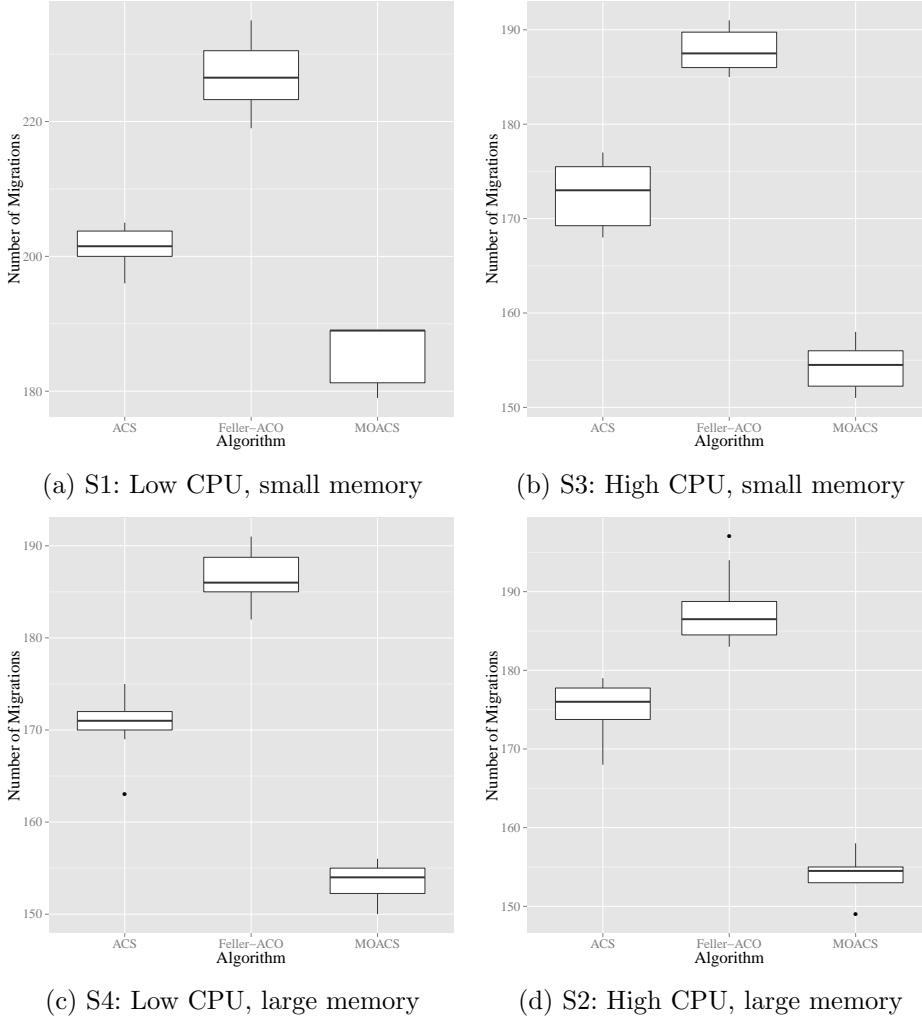
(a) S1: Low CPU, small memory

(b) S3: High CPU, small memory

(c) S4: Low CPU, large memory

(d) S2: High CPU, large memory

Figure 3.: Number of VM migrations

4.3.3 Execution Time and Scalability

The last comparison attribute is the execution time required by each solver to find a near-optimal, global best migration plan. Ideally, the solvers should use as less time as possible. Figure 4 presents the execution time for the ACS, MOACS, and Feller-ACO solvers when solving problems based on Scenario 2 with the number of PMs varying from 50 to 500 in increments of 50 and the number of VMs varying from 250 to 2500 in increments of 250.

We can observe in the figure that MOACS performed better than Feller-ACO. Moreover, ACS performed better than MOACS but, to be fair, it used a single-objective algorithm while MOACS explored the search-space for two different objectives.

For reference, we also report the execution times to solve Scenario 1 with $|P|$=100 and $|V|$=1000 in Table 6. For this scenario, ACS required a bit more than one minute. In contrast, MOACS required almost 2 minutes while Feller-ACO required almost 6 minutes. We report the median value for 10 test runs. However, we have observed that the standard deviation for the time variable was rather small for all solvers. The difference in the execution time between the MOACS and Feller-ACO solver is statistically significant (Wilcoxon Signed-Rank Test, p-value = 0.002).

Table 4.: Number of released PMs

		ACS	**MOACS**	Feller-ACO	Change	p-value
Scenario 1	Median Released	9	15	11	136%	0.005
	Sd Released	0.63	0.52	0.82		
	Packing Efficiency %	9%	15%	11%		
Scenario 2	Median Released	7	11	8	137%	0.005
	Sd Released	0.67	0.67	0.99		
	Packing Efficiency %	3.5%	5.5%	4%		
Scenario 3	Median Released	7	10	8	125%	0.004
	Sd Released	0.67	0.52	0.82		
	Packing Efficiency %	3.5%	5%	4%		
Scenario 4	Median Released	7	11	8	137%	0.005
	Sd Released	0.88	0.88	0.74		
	Packing Efficiency %	3.5%	5.5%	4%		

Table 5.: Number of VM migrations

		ACS	**MOACS**	Feller-ACO	Change	p-value
Scenario 1	Median Migrations	201.5	189	226	83%	0.002
	Sd Migrations	3.13	4.77	5.23		
Scenario 2	Median Migrations	176	154.5	186	83%	0.006
	Sd Migrations	3.37	2.31	4.52		
Scenario 3	Median Migrations	173	154.5	187.5	82%	0.005
	Sd Migrations	3.34	2.58	2.35		
Scenario 4	Median Migrations	171	154	186	83%	0.006
	Sd Migrations	3.14	2.07	0.74		

4.4   Analysis

We can observe that the proposed MOACS algorithm and its corresponding solver outperformed Feller-ACO in all the measured variables: number of released PMs and packing efficiency (change 125%), number of VM migrations (change 82%), and execution time (speedup 2.97X). The solvers were exercised in four different scenarios involving different VM requirements. Each scenario was evaluated in 10 independent test runs. The differences were statistically significant for all variables (Wilcoxon Signed-Rank Test, p-values less than or equal to 0.006).

The differences in the performance can be explained by the design of each algorithm. Feller-ACO uses a single-objective, single-colony MMAS algorithm with an AOF that combines two different objectives concerning the number of released

Table 6.: Execution time (in minutes) for the three solvers for Scenario 1

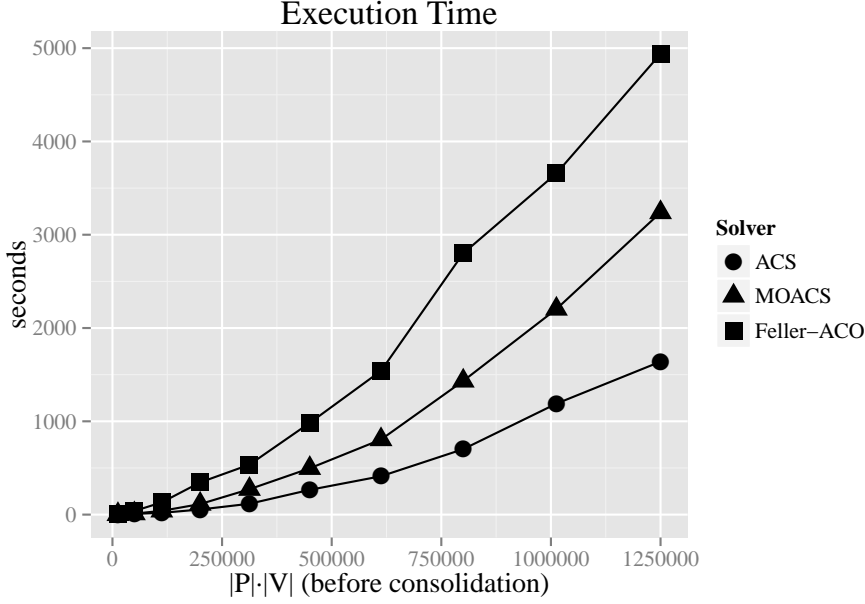|		ACS	**MOACS**	Feller-ACO	Speedup	p-value
$|P| \cdot |V|$=100000	Median Time	1.03	1.99	5.92	2.97X	0.002
	Sd Time	0.03	0.08	0.17		

Figure 4.: Scalability of the ACS, MOACS, and Feller-ACO solvers

PMs and the number of VM migrations, whereas MOACS uses a multi-objective algorithm with two independent ant colonies for optimizing the two objectives. The AOF approach in Feller-ACO uses several parameters to determine the relative importance of the two objectives in the overall optimization process. We consider that this approach has two drawbacks: (1) it is difficult to find appropriate values for the different parameters in an AOF and (2) an AOF may not combine the different objectives in an appropriate manner. For instance, as described in Section 3, maximizing the number of released PMs takes precedence in MOACS over minimizing the number of VM migrations. However, the AOF in Feller-ACO does not support precedence of one objective over another. Finally, MOACS uses additional constraints over its search-space, which significantly reduce the algorithm execution time without compromising on the quality of the solutions. The experimental evaluation clearly showed that these design decisions have an actual impact on the performance of the solvers.

It was also interesting to compare MOACS to ACS. MOACS clearly released more PMs and required less VM migrations than ACS. However, it was slower than ACS. When comparing ACS and Feller-ACO, we observed that ACS was faster and required less VM migrations than Feller-ACO, although it did not achieve the same packing efficiency. Still, ACS was the fastest of the three solvers and it can be a good alternative to consider when execution time is critical.

5.   Conclusion

We presented a novel multi-objective ant colony system algorithm for virtual machine (VM) consolidation in cloud data centers. The proposed algorithm builds VM migration plans, which are then used to reduce the number of required physical machines (PMs) by migrating and consolidating VMs on under-utilized PMs. It optimizes two objectives that are ordered by their importance. The first and foremost objective in the proposed algorithm is to maximize the number of released PMs. Moreover, since VM migration is a resource-intensive operation, it also tries

to minimize the number of VM migrations.

The proposed algorithm was evaluated in a series of experiments. The experimental evaluation compared the proposed algorithm with two previously published ant colony optimization based VM consolidation algorithms, which were chosen for comparison due to their excellent performance with respect to different attributes. We considered four different scenarios of interest to test the three algorithms under different VM configurations. The experimental results showed that the proposed algorithm provided an efficient solution for VM consolidation in cloud data centers. Moreover, it outperformed the two existing ant colony optimization based VM consolidation algorithms in terms of number of released PMs, packing efficiency, and number of VM migrations.

Acknowledgements

References

[1] T. Kaur and I. Chana, *Energy efficiency techniques in cloud computing: A survey and taxonomy*, ACM Computing Surveys 48 (2015), pp. 22:1–22:46.

[2] T. Mastelic, A. Oleksiak, H. Claussen, I. Brandic, J.M. Pierson, and A.V. Vasilakos, *Cloud computing: Survey on energy efficiency*, ACM Computing Surveys 47 (2014), pp. 33:1–33:36.

[3] A. Beloglazov and R. Buyya, *Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in cloud data centers*, Concurrency and Computation: Practice and Experience 24 (2012), pp. 1397–1420.

[4] F. Farahnakian, A. Ashraf, T. Pahikkala, P. Liljeberg, J. Plosila, I. Porres, and H. Tenhunen, *Using ant colony system to consolidate VMs for green cloud computing*, Services Computing, IEEE Transactions on 8 (2015), pp. 187–198.

[5] A. Beloglazov, J. Abawajy, and R. Buyya, *Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing*, Future Generation Computer Systems 28 (2012), pp. 755–768.

[6] A. Corradi, M. Fanelli, and L. Foschini, *VM consolidation: A real case based on OpenStack cloud*, Future Generation Computer Systems 32 (2014), pp. 118–127.

[7] T.C. Ferreto, M.A. Netto, R.N. Calheiros, and C.A.D. Rose, *Server consolidation with migration control for virtualized data centers*, Future Generation Computer Systems 27 (2011), pp. 1027–1034.

[8] S. He, L. Guo, M.M. Ghanem, and Y. Guo, *Improving Resource Utilisation in the Cloud Environment Using Multivariate Probabilistic Models*, in *Cloud Computing (CLOUD), 2012 IEEE 5th International Conference on*, 2012, pp. 574–581.

[9] I. Hwang and M. Pedram, *Hierarchical Virtual Machine Consolidation in a Cloud Computing System*, in *Cloud Computing (CLOUD), 2013 IEEE Sixth International Conference on*, 2013, pp. 196–203.

[10] X. Liao, H. Jin, and H. Liu, *Towards a green cluster through dynamic remapping of virtual machines*, Future Generation Computer Systems 28 (2012), pp. 469–477.

[11] A. Murtazaev and S. Oh, *Sercon: Server consolidation algorithm using live*

migration of virtual machines for green computing, IETE Technical Review 28 (2011), pp. 212–231.

[12] M. Marzolla, O. Babaoglu, and F. Panzieri, *Server consolidation in Clouds through gossiping*, in *World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2011 IEEE International Symposium on a*, 2011.

[13] M. Wang, X. Meng, and L. Zhang, *Consolidating virtual machines with dynamic bandwidth demand in data centers*, in *Proceedings of IEEE INFOCOM*, April, 2011, pp. 71–75.

[14] T. Wood, P. Shenoy, A. Venkataramani, and M. Yousif, *Sandpiper: Black-box and gray-box resource management for virtual machines*, Computer Networks 53 (2009), pp. 2923–2938.

[15] W. Vogels, *Beyond server consolidation*, ACM Queue 6 (2008), pp. 20–26.

[16] R.W. Ahmad, A. Gani, S.H.A. Hamid, M. Shiraz, A. Yousafzai, and F. Xia, *A survey on virtual machine migration and server consolidation frameworks for cloud data centers*, Journal of Network and Computer Applications 52 (2015), pp. 11 – 25.

[17] F.L. Pires and B. Barn, *A Virtual Machine Placement Taxonomy*, in *Cluster, Cloud and Grid Computing (CCGrid), 2015 15th IEEE/ACM International Symposium on*, May, 2015, pp. 159–168.

[18] F. Farahnakian, A. Ashraf, P. Liljeberg, T. Pahikkala, J. Plosila, I. Porres, and H. Tenhunen, *Energy-Aware Dynamic VM Consolidation in Cloud Data Centers Using Ant Colony System*, in *7th IEEE International Conference on Cloud Computing (CLOUD)*, 2014.

[19] C. Blum, J. Puchinger, G.R. Raidl, and A. Roli, *Hybrid metaheuristics in combinatorial optimization: A survey*, Applied Soft Computing 11 (2011), pp. 4135 – 4151.

[20] M. Harman, K. Lakhotia, J. Singer, D.R. White, and S. Yoo, *Cloud engineering is search based software engineering too*, Journal of Systems and Software 86 (2013), pp. 2225 – 2241.

[21] E. Feller, C. Morin, and A. Esnault, *A case for fully decentralized dynamic VM consolidation in clouds*, Cloud Computing Technology and Science, IEEE International Conference on (2012), pp. 26–33.

[22] M. Ferdaus, M. Murshed, R. Calheiros, and R. Buyya, *Virtual machine consolidation in cloud data centers using ACO metaheuristic*, in *Euro-Par 2014 Parallel Processing*, F. Silva, I. Dutra, and V. Santos Costa, eds., Lecture Notes in Computer Science, Vol. 8632, Springer International Publishing, 2014, pp. 306–317.

[23] M. Dorigo, G. Di Caro, and L.M. Gambardella, *Ant algorithms for discrete optimization*, Artif. Life 5 (1999), pp. 137–172.

[24] X.B. Hu, M. Wang, and E.D. Paolo, *Calculating complete and exact pareto front for multiobjective optimization: A new deterministic approach for discrete problems*, IEEE Transactions on Cybernetics 43 (2013), pp. 1088–1101.

[25] M. Dorigo and L. Gambardella, *Ant colony system: a cooperative learning approach to the traveling salesman problem*, Evolutionary Computation, IEEE Transactions on 1 (1997), pp. 53–66.

[26] L.M. Gambardella, É. Taillard, and G. Agazzi, *MACS-VRPTW: A multiple ant colony system for vehicle routing problems with time windows*, in *New Ideas in Optimization*, D. Corne, M. Dorigo, and F. Glover, eds., McGraw-Hill, London, UK, 1999, pp. 63–76.

[27] A. Ashraf and I. Porres, *Using Ant Colony System to Consolidate Multiple Web Applications in a Cloud Environment*, in *22nd Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP)*,

2014, pp. 482–489.

[28] P.Y. Yin and J.Y. Wang, *Ant colony optimization for the nonlinear resource allocation problem*, Applied Mathematics and Computation 174 (2006), pp. 1438 – 1453.

[29] S.K. Chaharsooghi and A.H.M. Kermani, *An effective ant colony optimization algorithm (ACO) for multi-objective resource allocation problem (MORAP)*, Applied Mathematics and Computation 200 (2008), pp. 167–177.

[30] Y. Gao, H. Guan, Z. Qi, Y. Hou, and L. Liu, *A multi-objective ant colony system algorithm for virtual machine placement in cloud computing*, Journal of Computer and System Sciences 79 (2013), pp. 1230 – 1242.

[31] M. Mishra and A. Sahoo, *On Theory of VM Placement: Anomalies in Existing Methodologies and Their Mitigation Using a Novel Vector Based Approach*, in *Cloud Computing (CLOUD), 2011 IEEE International Conference on*, July, 2011, pp. 275–282.

[32] C. Wohlin, P. Runeson, M. Höst, M.C. Ohlsson, B. Regnell, and A. Wesslén, *Experimentation in Software Engineering*, 1st ed., Springer-Verlag Berlin Heidelberg, 2012.