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Energy Efficient Virtual Machine Placement With an Improved Ant Colony Optimization Over Data Center Networks

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ABSTRACT Virtualization has achieved widespread adoption in various fields. As one of the most significant technologies in network virtualization, an effective virtual machine placement can facilitate to improve resource utilization in data center networks and cut down the enterprises' operation cost. In this paper, we proposed an energy efficient virtual machine placement scheme, which pursued to reduce communication cost and power consumption over traffic-aware data center networks. To solve such an optimization problem, an improved ant colony optimization with adaptive parameter setting was presented to balance its fast convergence and robust search capability. Compared with existing algorithms, simulation results demonstrated that our scheme achieved improvements in power consumption and communication cost, and had a significant reduction in run time under different traffic patterns and configurations.

INDEX TERMS Ant colony optimization, data center networks, energy efficient, virtual machine placement.

I. INTRODUCTION

Recent years have witnessed a dramatic growth of cloud services, which facilitates the development of the Internet and the Internet of Things. Thanks to the cloud computing system, little effort is required for customers to access cloud services without deploying a complex infrastructure. To implement such a system, in which the cloud service provider operates a data center (DC), massive technologies are necessary. Virtualization, one of the most critical technologies, has become an indispensable technique in the operation of a cloud DC [1]. It provides a promising approach to make multiple applications running in different performance-isolated platforms — virtual machines (VMs), which could be placed on several physical machines (PMs) in data center networks (DCNs). Not only does it enhance the flexibility and performance of service, but also it improves resource utilization in DCNs.

With the growing popularity of virtualization, virtual machine placement (VMP) has drawn considerable attention in cloud computing, which addresses the issue of how to place VMs on PMs efficiently. Several efforts have been made from many different perspectives, such as the reduction of operation cost [2], traffic or network optimization [3], the improvement in revenue [4] and so on.

Due to the rapid development of cloud computing, DCs encounter skyrocketing power consumption and electricity bills [5]. Unfortunately, such a significant increase in power consumption has inhibited or restricted the sustainable development of cloud services and seriously troubled DC operators. Therefore, energy efficiency has become a crucial factor in large-scale cloud DC. Driven by economic profit and sustainable development, some work has focused on power consumption over cloud DCNs [6]–[8]. For instance, Ye *et al.* [9] designed a VMP scheme to minimize energy consumption and load variance, maximize resource utilization and improve the robustness of PMs.

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Although there have been several research efforts to improve the energy efficiency over DCNs, communication cost has not been widely explored in energy efficient virtual machine placement. In this paper, we focused on bridging the gap and exploring a trade-off between communication cost and power consumption over traffic-aware data center networks. With consideration of adaptive transmission rates at switch ports, we proposed an energy efficient VMP scheme, termed E^2VMP. Specifically, our target is to achieve an energy efficient VMP strategy under the consideration of the power consumption at adaptive switch ports. It has been proved NP-hard in [10]. To solve such a bi-objective optimization problem, an improved ant colony optimization with adaptive parameter setting (AP-ACO) is developed to balance its fast convergence and robust search capability.

The remainder of this paper is organized as follows. Section II presents the related work, and an energy efficient model of the VMP scheme is elaborated in Section III. Section IV develops the improved ant colony algorithm with the adaptive parameter setting in detail. It is then applied in Section V to various conditions. Experiments are undertaken to evaluate the effectiveness and the efficiency of E^2VMP, by comparing with the heuristic approaches such as first-fit decreasing (FFD) and with metaheuristic optimization algorithms such as ant colony optimization algorithm. Finally, Section VI draws conclusions and gives an outlook to future work.

II. RELATED WORK

We focus on an efficient VMP scheme based on ant colony optimization algorithm. Here we present three relevant topics of related work: VMP, energy-efficient technologies in DC, and heuristic algorithms for VMP.

A. VIRTUAL MACHINE PLACEMENT

Virtual machine placement, a process of mapping VMs to PMs, is indispensable for cloud computing. It is also an essential approach for improving power efficiency and resource utilization in cloud infrastructures. Therefore, the VMP problem has drawn a lot of attention, and several efforts have been made from many different perspectives, such as the reduction of operation cost, the improvement in the quality of service and so on.

In [11], a traffic-aware VMP scheme was proposed to focus on the improvement of the network scalability, which is solved by a two-tier approximate algorithm. Fang *et al.* proposed an algorithm, termed VM-Group Mapping [12], to optimize both VMP and traffic flow routing by turning off unnecessary elements as many as possible. The researchers in [13] investigated a multi-dimensional VM consolidation model to place VMs onto as few PMs as possible and solve this optimization problem by a simulated evolution search heuristic. With more communication intensive applications deployed in DCs, the consolidation of flows brings a new challenge: it might cause network failures. To solve this problem, a time-consuming heuristic algorithm for VMP had been investigated in [14] to keep network survivable. In [15], the authors introduced a service-oriented VMP scheme aiming to minimize the communication cost between VMs supporting the same type of services.

To narrow the gap between research prototypes and real-world applications, many researchers have tended to approximate by multiple-objective optimization. Gao *et al.* [16] proposed a VMP scheme to reduce total resource wastage and power consumption simultaneously. A power-aware and performance-guaranteed VMP was proposed to balance the trade-off between saving PM power and guarantee VM performance [17]. Li *et al.* [18] focused on minimizing energy consumption and maximizing resource utilization for virtual network placement, and employed two chemical reaction optimization algorithms to solve such a problem. In [19], the VMP problem was formulated as joint multiple objective optimizations. To solve such an optimization problem, researchers proposed the multi-level joint VM placement and migration algorithm to minimize resource usage and power consumption in DCs. Qin *et al.* [4] focused on the VMP for bandwidth-hungry applications and proposed a multi-objective Ant Colony System algorithm to maximize the revenue of communications and the power consumption of PMs. Differently, Hou *et al.* [20] concentrated on VMP over edge devices layer of Internet of Things and designed a VM scheduling and bandwidth planning algorithm to minimize the number of upgrade batches.

B. ENERGY EFFICIENT TECHNOLOGIES IN DATA CENTER

The energy consumed by DCs is considerable, so many energy efficient technologies should be applied to save such colossal expense. Some research targets at maximizing power capacity. For dynamically managing power in multi-tenant DCs, Ren in [21] proposed a market-based solution to optimize the utilization of IT resources (such as CPU or memory). In [22], the authors developed a mixed integer linear programming model to optimize VM allocation for the DC with additional consideration of the power consumed by communication fabric.

Differently, some other researches emphasis on minimizing power consumption. In [23], a framework, termed Mistral, was proposed to optimize both power consumption and performance benefits, with considering the cost of the search itself in its decision making. Li *et al.* presented a joint power optimization through VMP on servers with scalable frequencies and flow scheduling in DCNs [24]. In addition, to improve the energy efficiency of DCs, authors in [25] formulated the energy consumption in VMP problem as a profile-based optimization problem. In such an optimization model, time intervals and resource usage were taken into consideration to predict the workload.

In the same vein, the authors in [7] focused on energy efficiency for virtual network embedding over optical DCNs. In their work, a mixed integer linear programming model was developed with power consumption added to achieve energy efficiency and reduce the spectrum usage for survivable virtual network embedding. Dai *et al.* [8] aimed to reduce much energy on networking equipment by powering down communication ports and line-cards whenever the associated servers are powered down. Verma *et al.* [26] employed a modified intelligent water drop algorithm for dynamic provisioning of VMs on hosts, so that the total energy consumption of a DCN could be reduced in cloud computing environment.

C. HEURISTIC ALGORITHMS FOR VIRTUAL MACHINE PLACEMENT

VMP problem in [27] is an instance of the multi-dimensional bin-packing problem. One of the widely used algorithms to solve bin-packing problems is the First Fit Decreasing (FFD) algorithm. FFD is a classical bin-packing algorithm: the items are sorted in non-increasing order of their size, and then in this order the next item is always packed into the first bin where it fits [28]. FFD ensures that larger size items will be processed first. When it is applied to VMP problem, FFD enables VMs in decreasing order of resource utilization and places each VM into the first PM that has enough resource remaining.

Bin-packing has been proven as an NP-hard optimization problem [29], therefore effective and desirable algorithms are important to obtain solutions. To solve such a problem, the evolutionary computation and the swarm intelligence algorithms have been suggested due to their simple operation and fast convergence [30]. Among several heuristic algorithms, ant colony optimization algorithm and genetic algorithm are two of the most popular approaches.

To minimize the required PMs to support the current load, Feller *et al.* [31] proposed a max-min ant system meta-heuristic with a single objective. Besides, the authors in [32] designed a genetic algorithm for the VMP problem to minimize resource wastage, power consumption, and heat dissipation. In [16], Gao *et al.* introduced the ant colony optimization algorithm and applied it to reduce total resource wastage and power consumption simultaneously. The authors in [33] proposed a multi-objective optimization scheme based on the genetic algorithm aiming at maximizing server utilization. To minimize the communication cost between VMs, the work in [15] used Genetic Algorithm to seek an approximate optimal placement solution in such a single objective optimization. In order to accelerate the convergence of their heuristic algorithm, Tang *et al.* [34] improved the genetic algorithm with a local optimization procedure to solve such a VMP problem in DCs.

All these methods mentioned above could contribute to better performance of the DCN: either making efficient use of resources or reducing the energy consumption in DCNs. Thanks to these benefits, we can take advantage of a heuristic algorithm to improve our design.

III. ENERGY EFFICIENT VMP SCHEME

In this section, we present a VMP model and consider both server capacity constraint and the transmission rate of switch ports. Then we formulate the optimization problem that aims at reducing power consumption and communication cost.

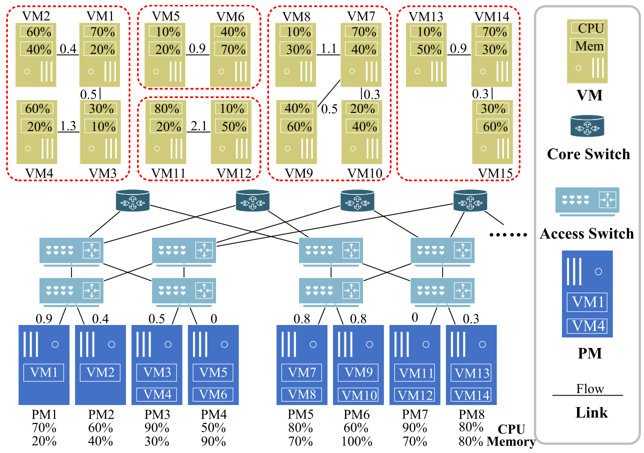

FIGURE 1. An example of VM placement strategy with adaptive port rate in a Fat-tree topology.

A. PROBLEM STATEMENT

To motivate and demonstrate the basic idea of our model, as shown in Fig. 1, we present a simple example of VMP in a Fat-tree topology with 4-port switches. For the sake of simplicity, the bandwidth and data rate are normalized by 100 Mbps. For instance, the number 0.5 in Fig. 1 equals 50 Mbps in reality. The numbers above the links between VMs represent the communication demand of VMs, and those above and under PMs represent the flow sizes through ports and the resource utilization of PMs respectively. Besides, only VMs in the same application, showing in the red box in Fig. 1, are able to complete data communication. When assigning VM_{15}, only PM_1 and PM_2 can hold it, and the distance from both PM_1 and PM_2 to PM_8 (which holds VM_{14}) are equal so that the communication cost is the same. Thus the power consumption becomes the determining factor.

It has been revealed in [35], [36] that energy consumption varies among different link rates at the switch in the real world. Moreover, power consumption was tested in [36], and the results showed that switches consume more power given increasing either link rates or the number of links. Hence, different from classic power-aware strategies, we consider not only the power consumption of PMs and switches but also that of switch ports. Considering that PM_1 and PM_2 are not idle before VM_{15} is assigned, the routing of the flow is similar in the network. Nonetheless, there is a big difference between their power consumption of the ports due to their various link rates. Specifically, if VM_{15} is placed PM_1 or PM_2, the port rate of PM_1 (that is 1.2) would be larger than that of PM_2 (0.7), resulting in more power consumption. With that in mind, we prefer PM_2 that consumes less power.

B. ENERGY EFFICIENT MODEL

Consider that there are V VMs that can be assigned to a DCN. In the DCN, it consists of P PMs and S switches equipped with K ports. $\mathbb{VM} = \{VM_v|1 \leq v < V\}$ and $\mathbb{PM} = \left\{PM_p|1 \leq p < P\right\}$ respectively represent the set of VMs and PMs. To indicate the mapping relationship between VM_v

TABLE 1. Notations.

Notation	Description
$\mathbb{PM}$	Set of PMs
$\mathbb{VM}$	Set of VMs
A_u^p	A binary decision for placing VM_u on PM_p
A_v^q	A binary decision for placing VM_v on PM_q
R_u	Resources requirement vector of VM_u
H_p	Resources capacity vector of PM_p
d_{pq}	Distance between PM_p and PM_q
s_{uv}	Size of communication flow between VM_u and VM_v
F_{sn}^{pn}	The flow size through the port pn at the sn^{th} switch
F_{max}	The maximum port rate (assuming identical in the network)
$Power$	Total power consumption
$Power_{PM}$	The power consumption of PMs
$Power_{DCN}$	The power consumption of DCNs
$Cost$	Total communication cost in the network
P_{port}	The power level of port
P_{PM}	The power of PM which is not idle
P_{Swi}	The power of switch which is not idle
Uti_{CPU}	The utilization of CPU
τ	Pheromone trail level
η	The heuristic information
$p_{u\to p}$	The probability of assigning VM_u to PM_p
α	The weight of pheromone trail level
β	The weight of the heuristic information
M	The number of ants
C_{max}	The number of iterations

and PM_p, a binary variable A_v^p is introduced as follows.

$$A_v^p = \begin{cases} 1, & if\ VM_v\ is\ assigned\ to\ PM_p \\ 0, & otherwise \end{cases} \tag{1}$$

Table 1 summarizes several necessary notations in this paper. R_u is defined as the resource requirement vector of VM_u and H_p as the server-side resource capacity vector of PM_p. The distance between PM_p and PM_q is denoted as d_{pq}. Let s_{uv} denote the size of communication flow between VM_u and VM_v. In the DC, at its sn^{th} switch, the flow size through port pn is denoted as F_{sn}^{pn}, $(0 \le sn < S, 0 \le pn < K)$. It could be calculated according to the routing algorithm. Considering the port rate constraint, F_{sn}^{pn} should be less than the maximum transmission rate F_{max}.

In DCNs, power consumption by computing nodes mostly depends on the CPU, memory and disk storage, of which CPU power consumption is dominant. In this paper, we focus on the dominant power consumption at PMs and assume that it has a linear relationship with CPU utilization, similar to related works [14], [16]. According to [36], different rates of switch ports consume power at different levels, then the power model could be calculated as follows.

$$\begin{aligned} Power &= Power_{PM} + Power_{DCN} \\ &= \sum_{All\ PMs} (P_{PM} + k \times Uti_{CPU}) \\ &\quad + \sum_{All\ Switches} (P_{Swi} + \sum_{port=0}^{K} P_{port}) \end{aligned} \tag{2}$$

where k is a constant factor obtained from the experiment in [14]. $Power_{DCN}$ represents the power consumption of PMs. $Power_{DCN}$ is the power consumption of DCNs and equal to the switch power plus the ports' power. The power level of port is denoted as P_{port}. Uti_{CPU} means the CPU utilization.

Moreover, the communication cost could be obtained by the following:

$$Cost = \sum_{p,q=1}^{P} \sum_{u,v=1}^{V} s_{uv} \cdot d_{pq} \cdot A_u^p \cdot A_v^q. \tag{3}$$

where s_{uv} is the size of communication flow between VM_u and VM_v, d_{pq} is the distance between PM_p and PM_q. Let A_u^p be a binary variable that takes the value 1 if VM_u is placed on PM_p; otherwise, the value is 0. And A_v^q is the same to A_u^p.

Thus, the multi-objective problem is formulated as following:

$$minimize \quad (Power, Cost) \tag{4}$$

The objective function has two terms: one is aimed at minimizing the total power consumption, and the other is to minimize the total communication cost. The ultimate goal of the objective is to minimize the whole consumed energy and the optimized mapping solution to achieve a trade-off between power consumption and communication cost.

Besides, the model has some constraints. It is subject to the following equations:

$$\sum_{p=1}^{P} A_u^p = 1, \quad \forall u \in [0, V), \tag{5}$$

$$\sum_{u=1}^{V} A_u^p \cdot R_u \le H_p, \quad \forall p \in [0, P), \tag{6}$$

$$F_{sn}^{pn} \le F_{max}, \quad \forall switch \in [0, S), \ \forall port \in [0, K) \tag{7}$$

Equation (5) states that each VM must be assigned to one and exactly only one PM. Equation (6) presents the capacity constraint of PMs to ensure the resources are available to VMs. Equation (7) is the limitation of ports to avoid overload and congestion. Given n VMs to be assigned to m PMs, there are m^n possible solutions in all. It is completely impractical to make an enumeration of all solutions to find the best one. In the next section, we apply E^2VMP and improve ant colony algorithm to search for near-optimal solutions.

IV. HEURISTICS ALOGRITHM

VMP problem has been proven as an NP-hard problem which is difficult to find a solution in polynomial time. Therefore, effective and desirable algorithms are important to obtain solutions. To solve our energy efficient VMP scheme (E^2VMP) with bi-objective function, an improved ant colony optimization with adaptive parameter setting, termed AP-ACO is proposed to improve its convergence rate and search capability.

The pseudo-code of E^2 VMP is depicted in Algorithm 1. E^2VMP works in three stages: in the initialization stage, all the parameters are initialized, and every pheromone trail is set as τ_0. In the iterative step, the number of ants and two critical

Algorithm 1 E^{2}VMP With AP-ACO Algorithm

Require:
Number of PMs: P; Number of VMs: V; Number of cycles: C_{max};
Distance between PM_p and PM_q: d_{pq}; Available resource of PM_p: a_p; Resource request of VM_v: r_i.
Ensure:
VM placement solution

```
/*Initialization*/
Set values of parameters: P, V, C_max, ρ;
Initialize values of α, β, and M;
Initialize Pareto set S_opt;
Run FFD algorithm to obtain Power_S0 and Cost_S0;
/*Iteration*/
for each t ∈ [1, C_max] do
    for each ant ∈ [1, M] do
        for each v ∈ [1, V] do
            Update the heuristic information;
            for each p ∈ [1, P] do
                if r_v < a_p then
                    Calculate the probability p_{v→p} according to Eq.(15);
                end if
            end for
            Generate a random number q for "roulette wheel" selection;
            if q < p_{v→p} then
                Place VM_v to PM_p;
            end if
        end for
        Add the current solution in S_opt;
    end for
    // Construct optimal solution set
    Remove dominated solutions in S_opt;
    Update pheromone information τ_{i→p} according to Eq.(10);
    Adjust α, β and M according to Eq.(16)-(18);
    t++;
end for
/*Iteration end*/
Return S_opt
```

factors of ant colony algorithm will change according to the last iteration. Then the artificial ants start assigning VMs to PMs with calculated probability. The probability is based on the pheromone trail and the heuristic information which leads ants to the promising VM placement configuration. In the end, we can get the Pareto set by removing the dominated solutions.

A. HEURISTIC INFORMATION

The heuristic information is the main difference between a real ant and an intelligent ant. In a real ant colony, ants select their path with equal probability at the first beginning. Differently, artificial ants can make use of the heuristic information when they are searching for the optimal solution. The heuristic information $\eta_{v\to p}$ indicates the desirability of assigning VM v to PM p. To assess the desirability of each move accurately, the heuristic information is dynamically computed according to the current state of the ant. The way ants release the heuristic information will influence the algorithm. Therefore, we should efficiently execute the algorithm. The proposed method to calculate the heuristic information considers the partial contribution of each move to the objective function value.

With arranging all VMs randomly in an order called VO and assigned VMs one by one to ideal PMs, we can calculate the partial contribution of assigning VO_u to PM_p for the communication cost according to the following equation:

$$\eta_{u\to p}^{cost} = \frac{1}{\varepsilon + \sum\limits_{w=1}^{v} \frac{s_{uw}\cdot d_{pq}}{Cost_{S_0}}}, \quad A_u^p = 1 \; and \; A_w^q = 1. \tag{8}$$

Similarly, we can calculate the partial contribution of assigning VO_u to PM_p for the power consumption as follow:

$$\eta_{u\to p}^{power} = \frac{1}{\varepsilon + 1/Power_{S_0}}, \tag{9}$$

where $Cost_{S_0}$ and $Power_{S_0}$ respectively represent the total communication cost and the power consumption of the solution S_0 generated by the FFD algorithm [37]. And ε is a very small constant which can be defined as 0.00001.

B. PHEROMONE TRAIL UPDATE

The pheromone trail is another vital element of the probability of assigning VO_u to PM_p. The value of pheromone trail may increase, due to the secretion and diffusion or decrease, as the evaporation. While the secretion of pheromone guides E^{2}VMP to a better solution, the evaporation also plays an important role. It avoids a too rapid convergence towards a suboptimal result, thus encouraging the ants to search for a better solution. In the initialization phase, the initial pheromone level is set as τ_0. In the iterative part, the pheromone trail should be updated before reiterating the process. Let $\rho(0 < \rho < 1)$ denote the pheromone evaporating parameter, we can get the total pheromone trail of iteration $t-1$:

$$\tau_{u\to p}(t) = (1-\rho)\cdot\tau_{u\to p}(t-1) + \Delta\tau_{u\to p}, \tag{10}$$

where $\Delta\tau_{u\to p}$ represents the increment of the total pheromone trail.

Different from most ant colony algorithms, we employ a pheromone diffusion model to simulate the real ant colony. In the classic algorithm, the pheromone concentration becomes a character of PM_p and does not affect other PMs. The information exchange among ants is insufficient and not in time. Considering the diffusion, we can improve the collaboration among ants and reduce the times of iteration. The diffusion model approximately subjects to Gaussian plume model. Therefore, we enhance the pheromone of the PM whose objective function value is relatively small. Moreover, the other PMs that are close to the selected PM will also obtain pheromone. Hence $\Delta\tau_{u\to p}$ can be calculated as follows:

$$\Delta\tau_{u\to p} = \sum_{k=1}^{M} \Delta\tau_{u\to p}^{k}, \tag{11}$$

where M is the number of ants and $\Delta\tau_{u\to p}^{k}$ represents the pheromone increment that ant k leaves if VM_u is placed to PM_p.

In the following, we will illustrate how to build $\Delta\tau_{u\to p}^{k}$. According to the reality, the peak of pheromone appears at the selected PM, so the expectation of the Gaussian distribution is related to d_{pq}. In AP-ACO, a better solution is expected to obtain more pheromone, so the peak of a better solution should be higher. In other words, the variance is smaller. According to the demands above, we can define $\Delta\tau_{u\to p}^{k}$ as shown, in which Obj_{best} represents the function value of the best solution until this iteration:

$$\Delta\tau_{u\to p}^{k} = \begin{cases} \dfrac{1}{Obj_{best}\sqrt{2\pi}}, & A_u^p = 1 \\ \dfrac{1}{Obj_{best}\sqrt{2\pi}} \cdot \exp\left\{-\dfrac{{d_{pq}}^2}{2\cdot {Obj_{best}}^2}\right\}, & A_u^p \neq 1. \end{cases} \tag{12}$$

To avoid search stagnation, the pheromone intensity is defined with upper and lower limits: $T_{\max}$ and $T_{\min}$, which can be calculated as follows:

$$T_{\max} = \frac{1}{1-\rho} \times \frac{1}{B}, \tag{13}$$

$$T_{\min} = \frac{1}{5} \cdot T_{\max}, \tag{14}$$

where ρ denotes the pheromone evaporating parameter, and B represents the value of the objective function corresponding to the optimal solution at the end of the current iteration.

C. ADAPTIVE PARAMETER SETTING

After defining the pheromone trail and heuristic information, let $p_{u\to p}$ denote the probability of assigning VM_u to PM_p. Define the set of all available PMs for VM_u as $\mathbb{A}$, we can easily calculate $p_{u\to p}$ as follow:

$$p_{u\to p} = \frac{\left[\tau_{u\to p}(t)\right]^{\alpha} \cdot \left[\eta_{u\to p}\right]^{\beta}}{\sum_{q} \left[\tau_{u\to q}(t)\right]^{\alpha} \cdot \left[\eta_{u\to q}\right]^{\beta}}, \quad PM_q \in \mathbb{A} \tag{15}$$

where α and β represent the pheromone concentration and the weight of the heuristic function respectively.

From Eq. 15, we can infer that the value of the α and β will affect the algorithm performance to a large extent. When the β is bigger, and α is smaller, the state transition probability is greatly influenced by heuristic information. In such a condition, although the algorithm convergence speed would increase, the result is often inferior. On the other hand, in the reverse situation, the state transition probability is greatly influenced by pheromone, which usually makes it difficult to find the optimal solution in limited iterations. To pursue a more robust search and faster convergence on the optimum solution, the parameters (α and β) should be adjusted adaptively.

At the same time, the number of ants M has a significant impact on the performance of the traditional algorithm as well. If the number of ants is large, the global search ability and stability of the algorithm can be improved at the cost of a slower convergence. On the contrary, a smaller value of M will result in algorithm premature stagnation due to falling into partial optimization. To improve its convergence and decrease the degrees of the precocity and stagnation, the parameters α, β, and M are adjusted adaptively. They all follow the logistic sigmoid function:

$$\alpha = \frac{\alpha_{\max} - \alpha_{\min}}{1 + e^{-\frac{\frac{C_{\max}}{2} - C}{P}}} + \alpha_{\min}, \tag{16}$$

$$\beta = \frac{\beta_{\max} - \beta_{\min}}{1 + e^{-\frac{\frac{C_{\max}}{2} - C}{P}}} + \beta_{\min}, \tag{17}$$

$$M = (\text{int})\frac{M_{\max} - M_{\min}}{1 + e^{-\frac{\frac{C_{\max}}{2} - C}{P}}} + M_{\min}, \tag{18}$$

where $C_{\max}$ denotes the upper limit of iterations and C represents the current iteration. P is a parameter that can be dynamically adjusted, and its value determines how quickly the size and parameters change with different values of C.

D. PARETO FRONT

To solve multi-objective optimization problems, several objectives are required to be considered simultaneously. However, due to conflicts and incomparability between those targets, the best solution for one target may be the worst for another one. In addition, in practice, there is no single best solution for the problem but a set of solutions that are superior when all objectives are considered [38].

The Pareto approach is more often used to cope with multi-objective problems than the conventional weighted-formula approach. The solution set is known as a non-dominated solution set. If the corresponding objective vectors of some solutions, which contain all decision vectors, cannot be improved in any dimension without degradation, the set of such solutions can be considered as Pareto optimal, which constitutes the so-called Pareto front [39]. For a given system, the Pareto front or Pareto set is the set of parameterizations (allocations) that are all Pareto efficient. Finding Pareto front is particularly useful in engineering. By yielding all of the potentially optimal solutions, a designer can focus tradeoffs within this constrained set of parameters, rather than considering the full ranges of parameters.

V. PERFORMANCE EVALUATION

A. SIMULATION SETUP

In this section, we use some simulation experiments to evaluate the performance of the proposed algorithm. The settings

TABLE 2. Parameters.

Parameter	α	β	M
Range	[0.1,5]	[1,10]	[50,70]

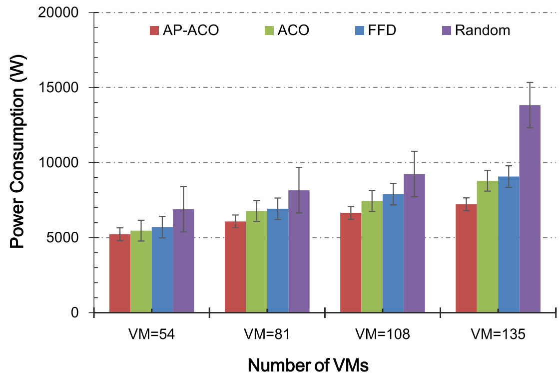

FIGURE 2. Performance comparison on power consumption with different VM numbers.

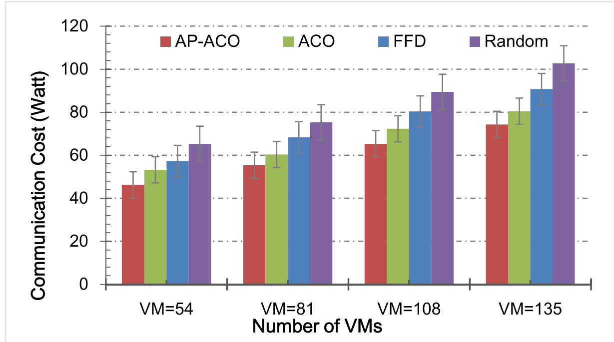

FIGURE 3. Performance comparison on communication cost with different VM numbers.

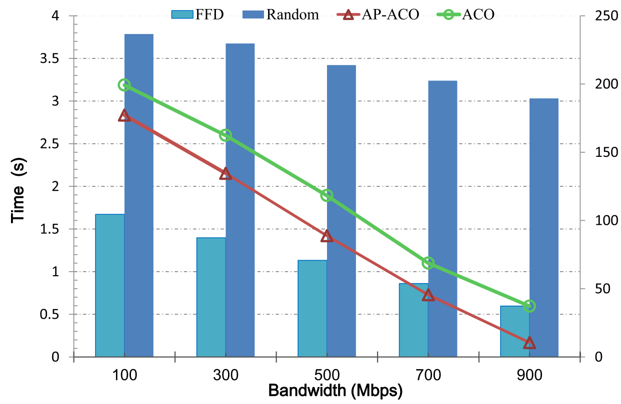

FIGURE 4. Comparison on run time.

of various parameters have a direct effect on the algorithm performance.

According to preliminary experiments, the pheromone evaporating parameter determined to be $\rho = 0.7$, and constant parameter P equals 30. The variable parameters are initialized as $M = 40$, $\alpha = 0.1$ and $\beta = 5$. The range of parameters can be seen in Table 2. Also, we generated a Fat-tree network that includes 54 PMs and 45 switches. According to [40], we consider the VM resource requirements are uniformly distributed in [0.2, 0.6]. Since the DC traffic is quite different from Internet traffic and it is often unavailable, recent studies [41] have proposed some good characterization on workload and traffic in DCNs. According to their studies, we constructed a synthesized workload emulating the traffic. For simplification, we assumed the traffic demands of VMs meet the normal distribution.

B. SIMULATION RESULTS AND DISCUSSION

In this section, we will prove that AP-ACO is efficient under different traffic patterns and configurations. We will compare the performances of AP-ACO with three other algorithms: Basic ACO algorithm, FFD algorithm and Random algorithm. Each test below is repeated with 100 runs, and the average results over 100 independent runs are shown in figures.

First, we experimented by placing 108 VMs in the Fat-tree topology to compare four algorithms by calculating the values of objective functions separately. In order to simplify the calculation, the experiment [14] shows that the power consumption of PMs can be described by a linear relationship between the power consumption and CPU utilization, which is $Power_{PM} = 86.495 + 0.311 \times Uti_{CPU}$.

In order to get a better understanding of the comparison among these algorithms, we compared them from two aspects: power consumption and communication cost. The results can be seen in Fig. 2 and Fig. 3.

From Fig. 2 and Fig. 3, we can see that the power consumption and communication cost are increasing when the number of VMs is larger. In the same network topology, due to the increase of VMs, more PMs are in the active model, which will cost more energy. Also, when more VMs work, the resource requirements will increase, leading to a large communication cost. In addition, from the two figures above, we can conclude that AP-ACO is the best algorithm among the four. Obviously, the performance of Random algorithm is the worst in that it is not able to find the best VMP without using any technics. The ACO algorithm outperforms FFD algorithm, because the ACO algorithm can search the solution space more efficiently and globally. Furthermore, the AP-ACO performs better than ACO algorithm, which demonstrates the adaptive parameter setting and Pareto set are efficient.

As we can observe from the Fig. 4, the time decreases with the increase of bandwidth. This phenomenon can be explained by the following reasons: when the communication demand of VMs and flow sizes through ports are constant, the wider the bandwidth is, the larger the amount of data is transmitted per unit of time. We can also see that the meta-heuristic optimization algorithms (*ACO* and AP-ACO) spend a longer time than those of FFD algorithm and Random. This results from the design of ACO-based algorithms. The movement of ants will be calculated every iteration, which would

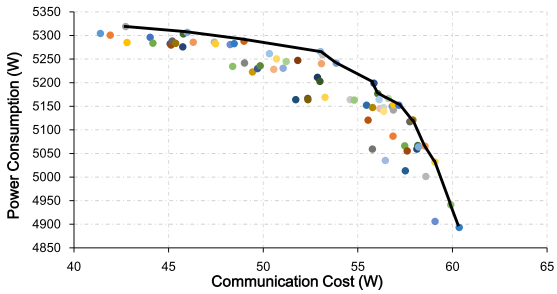

FIGURE 5. Pareto frontier for communication cost and power consumption.

consume a lot of time. Also, AP-ACO uses the result of FFD as an initial feasible solution, it is reasonable that the run time of AP-ACO is longer than that of FFD, but shorter than ACO. In addition, AP-ACO with adaptive parameter setting pursues to balance its fast convergence and robust search capability, which is the other reason for less time compared with the classic ACO. Also, the Random algorithm just assigns VMs to PMs in an unpredictable order, so mapping might fail and should try again. Therefore, the Random algorithm will consume more time than FFD algorithm. From the above analysis, though AP-ACO would take a longer time for computation, it can achieve the best performance.

In Fig. 5, we can see the Pareto front of AP-ACO. It is formed by the point where the Pareto optimal solution is mapped from the decision variable space to the target function space. This figure shows that our algorithm can achieve the Pareto optimal solutions, and solutions are uniformly distributed along the Pareto frontier. As every solution in the Pareto set cannot make any improvement without weakening at least one objective, we can infer that the Pareto solutions can make a tradeoff between communication cost and power consumption. Therefore, the best VMP can be chosen according to the practical factors.

VI. CONCLUSION AND FUTURE WORK

This paper addresses an issue of energy-efficient VMP problem by a scheme, termed E^2VMP. It formulates the VMP as a bi-objective optimization problem and solves the VMP problem based on ant colony optimization. In pursuit of fast convergence and robust search capability, we improve the ant colony optimization algorithm, named AP-ACO, to find the best solution of the placement. The performance of our proposed scheme is evaluated in comparison with FFD algorithm and Random algorithm. From the simulation, we prove that the proposed algorithm could find the best solution at the cost of run time. The results show that E^2VMP is adaptable to different configurations and efficient to different traffic patterns.

However, there are still a few limitations in our work. The first one is that we just focus on CPU power consumption, which is the dominant consumption. Further extension of power consumption is left out of consideration and left for our further study. The other one is that we do not evaluate VMP algorithms with real trace data of the cloud platform. In the future, we will extend our experimental results through trace-driven simulation, in order to evaluate our VMP algorithm. Furthermore, we will concern methodology to reduce computational time and explore a more effective solution to cut down power consumption and communication cost.

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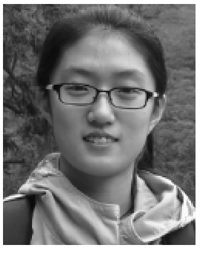

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