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The Virtual Machine Migration Strategy Based on Dynamic Threshold

Jin Yang[1,*]

[1]School of Computer Science, Guangdong Business and Technology University, Zhaoqing, Guangdong, China
[*]Corresponding author: yjcloud2022@126.com

Abstract: *With the rapid development of cloud computing, virtualization is widely used in data centers for resource management. However, traditional static threshold-based virtual machine migration strategies struggle to adapt to changing workloads. To address this, we propose a dynamic threshold-based strategy that monitors resource utilization to optimize migration timing and reduce costs. Simulation experiments on a real data center confirm the superior performance of our approach compared to static methods. This intelligent and efficient strategy enhances resource management, and energy efficiency in data centers.*

Keywords: *Cloud computing, Dynamic thresholds, Energy efficiency*

1. Introduction

Cloud computing technology is a method of providing all services to customers through the Internet. With this technology, customers are able to rent the required services through web browsers. Cloud computing has three service models, namely Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS) [1]. Cloud computing services are deployed on large-scale cloud data centers, typically consisting of millions of physical machines. These data centers utilize virtualization technology to provide users with customizable, highly reliable, and scalable virtual machine resources[2]. With the rapid growth of the cloud computing industry, the demand from users has significantly increased. There is a growing emphasis on dynamic resource management, elasticity, and automation. However, this surge in demand has led to a sharp increase in energy consumption within cloud computing data centers. Unfortunately, the current calculation resource utilization in data centers remains relatively low. The average resource utilization in most data centers is as low as 20%[3]. Moreover, idle nodes account for over 70% of peak power consumption[4].

In cloud computing, the importance of resource utilization cannot be overlooked. Virtual machine consolidation technology is one of the crucial research focuses for improving resource utilization.

By dynamically consolidating virtual machines, inactive hosts in the data center can be set to power-saving mode, reducing the number of active hosts in the data center and achieving energy savings [5]. Tran et al. [6] proposed the V2PQL virtual machine migration algorithm, and simulation results validated its effectiveness. The method consists of a training phase and an extraction phase. The V2PQL algorithm was compared with Round-Robin, Reverse Ant System, Maximum Minimum Ant System, and Ant System algorithms to highlight its advantages and feasibility in the extraction phase. Khan et al. [7] proposed a hybrid optimization algorithm for virtual machine migration in cloud environments. By combining the Cuckoo Search Optimization Algorithm and Particle Swarm Optimization Algorithm, the proposed hybrid optimization model was obtained. The main goals of this research were to reduce energy consumption, computation time, and migration costs. Belgace et al. [8] proposed the VMLM algorithm based on an improved virtual machine migration process and selection. Benchmark tests were conducted against the JVCMMD and EVSP solutions. Simulation experiments validated the effectiveness of this method, which includes two stages: machine learning preparation stage and virtual machine migration stage. Kaur et al. [9], based on the SESA Elastic Scheduling Algorithm, proposed a more energy-efficient virtual machine allocation and migration algorithm. The proposed work used cosine similarity and bandwidth utilization as additional utilities to improve current performance QoS. Hummaida et al. [10] proposed a method for dynamically discovering CPU utilization during virtual machine migration. This approach monitors VM response time, identifies CPU thresholds when response time exceeds defined SLA levels, and uses these thresholds for VM migration. SLA violations were significantly reduced, and

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CPU utilization of active nodes improved. Singh et al. [11] proposed an energy-efficient multi-objective adaptive bat foraging optimization algorithm (MAMFO), optimizing factors such as energy consumption, CPU, memory, and other resource utilization. This method significantly improves resource utilization and energy efficiency.

In the process of virtual machine consolidation, the determination of the triggering timing for virtual machine migration is one of the key technologies in virtual machine consolidation. The research on triggering mechanisms can be classified into static threshold triggering mechanism and dynamic threshold triggering mechanism. However, the current threshold research utilizes a single mathematical model, while the historical load utilization variation of physical machines is highly complex. Using a single prediction method alone cannot be applicable to all situations.

The Three-way Decision Theory, a composite human cognitive processing strategy proposed by Yao [12], provide a more reasonable explanation for the three region of decision rough sets. In recent years, this theory has been widely applied in cloud computing [13-14], as there are also many "three" phenomena in cloud data centers. This paper divides the fluctuation of physical machine loads into three branches and uses different prediction methods to forecast the loads and adjust the thresholds accordingly, aiming to achieve energy savings.

Therefore, this paper proposes a virtual machine dynamic consolidation strategy based on the Three-way Decision Theory. Drawing on the relevant ideas of the Three-way Decision Theory, this method divides the historical fluctuations of physical machine loads into three branches and uses different prediction methods for load forecasting. Finally, it dynamically adjusts the thresholds based on the predicted loads to achieve more precise triggering timing for virtual machine migration. This method not only optimizes the number of computing nodes effectively but also reduces the frequency of migrations, aiming to save energy and improve resource utilization.

The remaining sections of this paper are organized as follows: Section 2 primarily introduces the problem description and the establishment of relevant models. Section 3 presents the design of the algorithm discussed in this paper. Section 4 proposes performance metrics and conducts comparisons and analysis of certain algorithms. Section 5 concludes the paper and discusses future work.

2. Related Work

2.1. One Exponential Smoothing Model

The formula for one exponential smoothing method is as follows:

$$F_{t+1} = \alpha Y_t + (1-\alpha)F_t,\ 0 \le \alpha \le 1 \tag{1}$$

Where, F_{t+1} represents the forecasted value at time $t+1$. F_t represents the forecasted value at time t. Y_t represents the observed value at time t. α is the smoothing coefficient, between 0 and 1.

2.2. Holt's double exponential smoothing model

The Holt's double exponential smoothing model is a commonly used time series forecasting model used to predict data with trends. This model is an extension of the exponential smoothing method and involves decomposing the time series data into level and trend components for prediction. The model is based on two parameters for smoothing: the level component and the trend component. The level component represents the long-term average level of the time series, while the trend component reflects the changing pattern of the time series. The formula for the Holt's double exponential smoothing model is as follows:

$$Level_t = \alpha * Y_t + (1-\alpha) * (Level_{t-1} + Trend_{t-1}) \tag{2}$$

$$Trend_t = \beta * (Level_t + Level_{t-1}) + (1-\beta) * Trend_{t-1} \tag{3}$$

$$\hat{Forcast}_{t+h} = Level_t + h * Trend_t \tag{4}$$

where, $Level_t$ is the updated level component at time t. Y_t is the observed value at time t. $Trend_t$

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is the updated trend component at time t. α is the smoothing parameter for the level component ($0 \le \alpha \le 1$). β is the smoothing parameter for the trend component ($0 \le \beta \le 1$). h is the forecast horizon or the number of periods ahead for forecasting. $\hat{Forcast}_{t+h}$ is the forecasted value at time $t+h$.

3. Proposed Methodology

The specific process of the dynamic consolidation strategy based on the three-way decision model is as follows: Firstly, calculate the fluctuation of the load history rate and analyze the historical data. Then, combine the relevant theories of the three-way decision model to partition the historical data into corresponding domains P_1, P_2, and P_3. The formula is as follows:

$$\begin{cases} P_1(X) = \{x \in OB \mid \Pr(X \mid [x]) \ge \alpha\} \\ P_2(X) = \{x \in OB \mid \alpha < \Pr(X \mid [x]) < \beta\}. \\ P_3(X) = \{x \in OB \mid \Pr(X \mid [x]) \le \beta\} \end{cases} \tag{5}$$

Following that, different prediction methods are employed for each domain to make predictions. The predicted results are then used to dynamically adjust the thresholds. Subsequently, the virtual machine selection strategy and virtual machine placement strategy are determined, as shown below:

(1) virtual machine selection strategy

The virtual machine selection strategy is based on the MCC(Maximum Correlation Coefficient) algorithm, which selects the virtual machines with the highest correlation in terms of CPU utilization with other virtual machines for migration. The multi-correlation coefficient for each X_i is denoted as $R^2_{X_i, X_1, \ldots, X_{i-1}, X_{i+1}, \ldots, X_n}$. The MC strategy identifies virtual machines that satisfy the conditions defined by equation (6). The formula for MCC is as follows:

$$v \in V_j \,\middle|\, \forall a \in V_j, R^2_{X_v, X_1, \ldots, X_{v-1}, X_{v+1}, \ldots, X_n} \ge R^2_{X_v, X_1, \ldots, X_{a-1}, X_{a+1}, \ldots, X_n} \tag{6}$$

(2) Virtual Placement Policy

FF(First Fit placement) is a policy that finds the first host with suitable resources to place a given virtual machine. It is an efficient time-based strategy, with a best-case complexity of O(1) and a worst-case complexity of O(N), where N represents the number of hosts. Additionally, such a policy is resource-efficient as it promotes server consolidation by attempting to place the maximum number of virtual machines on the same host, thereby increasing the utilization of host resources.

The virtual machine execution is completed. Its process is shown in Figure 1.

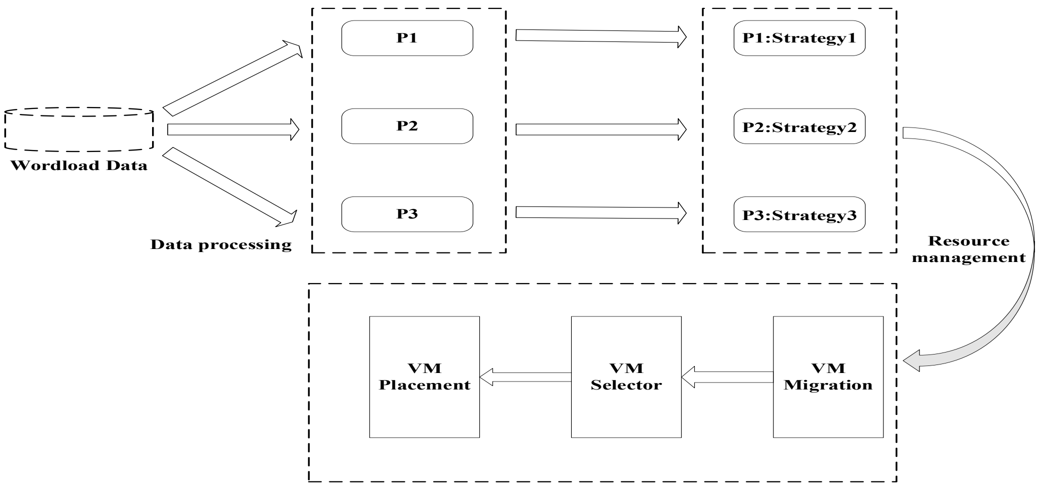

Figure 1: Flowchart

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Step 1: Calculate the load fluctuation value based on historical data. A low fluctuation value indicates that the data segment is relatively stable with minimal changes. A high fluctuation value indicates significant variations in the data.

Step 2: If the fluctuation value is low, use exponential smoothing to predict the load and determine the threshold.

Step 3: If the fluctuation value is high, apply Holt's double exponential smoothing to predict the load and determine the threshold.

Step 4: If the fluctuation value is neither high nor low, consider a global change scenario.

Step 5: Begin determining the virtual machine selection strategy and placement policy.

Step 6: Perform virtual machine migration until the tasks and virtual machines have completed execution.

4. Results

The simulation tool used in this study is the CloudSimPlus platform. CloudSimPlus is a cloud simulation framework based on CloudSim, designed for simulating and evaluating various resource management strategies and algorithms in cloud computing environments. It offers a range of functionalities and features. The dataset used in this study is the Google Clusters dataset.

Based on the experimental simulations, it can be observed from Figure 2 and Table 1 that the algorithm proposed in this paper demonstrates significantly lower energy consumption compared to the MMT-FF[15] and RS-FF[16] algorithms across different task quantities.

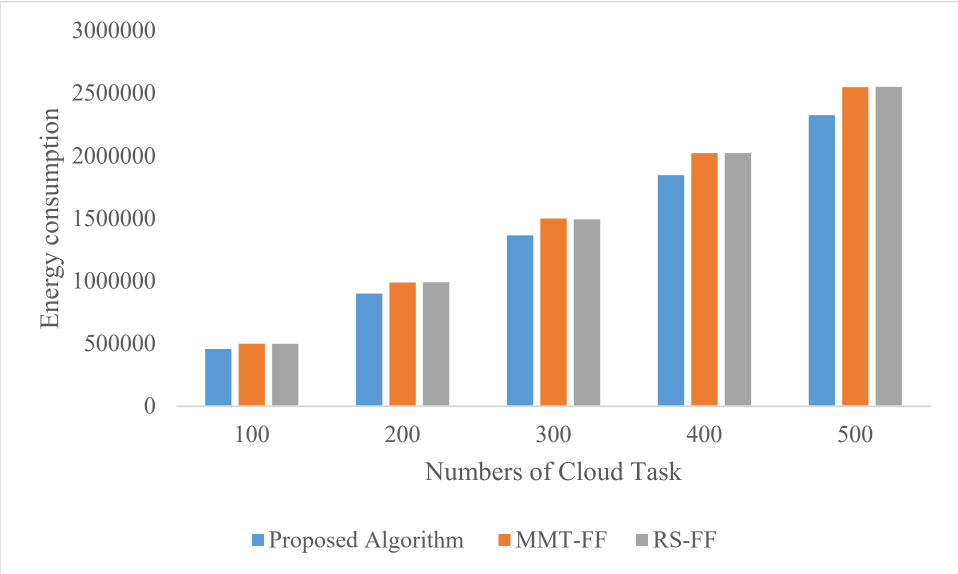

Figure 2: Comparison of Energy Consumption.

Table 1: Comparison of energy consumption.

Numbers of Cloud Task	Proposed Algorithm	MMT-FF	RS-FF
100	457223	499815	498380
200	899289	987331	990095
300	1364897	1498710	1492574
400	1845105	2022373	2022324
500	2324116	2548793	2550623

Based on the experimental simulations, it can be observed from Figure 3 and Table 2 that the algorithm proposed in this paper demonstrates significantly fewer virtual machine migration instances compared to the MMT-FF algorithm and RS-FF algorithm across different task quantities.

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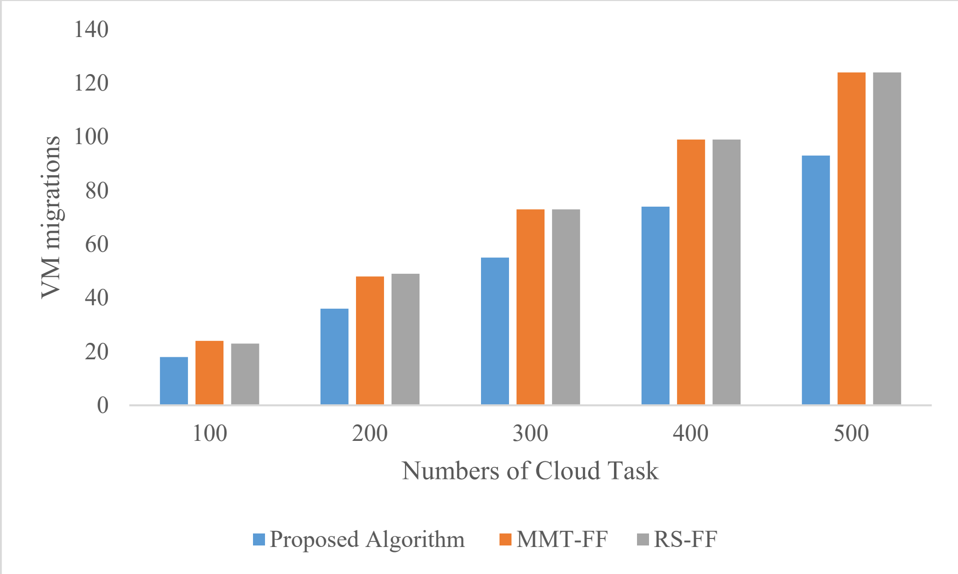

Figure 3: Comparison of Virtual Machine Migration times.

Table 2: Comparison of energy consumption.

Numbers of Cloud Task	Proposed Algorithm	MMT-FF	RS-FF
100	18	24	23
200	36	48	49
300	55	73	73
400	74	99	99
500	93	124	124

5. Conclusion

The Virtual Machine Migration Strategy Based on Dynamic Threshold is an effective approach for resource management. This study focuses on real-time adjustments of dynamic thresholds to adapt to changing workloads. Through simulation experiments, the proposed method demonstrates better energy consumption reduction compared to traditional static threshold methods. Future research can further optimize algorithms and models, explore additional virtual machine migration strategies, and apply these strategies to practical cloud computing environments.

Acknowledgements

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