Journal of Information Systems Engineering and Management
2025, 10(24s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Enhancing Cloud-Based Virtual Machine Migration and Consolidation with (UW-TBEA) Unpredictability-Weighted Time Backward Expectation Algorithm

[1*] Mohanaprakash T A, [2] Suma T , [3] Selvakumari S , [4] K.Sherin
[1] Department of CSE , CMR University, Bangaluru , tamohanaprakash@gmial.com
[2] Department of CSE , Sri Venkateshwara College of Engineering Bengaluru , India , suma.t_cse@svcengg.edu.in
[3] Department of Physics, Panimalar Engineering College, Chennai, India. selvi1977@gmail.com
[4]Department of CSE, St.Joseph's Institute of Technology, OMR , Chennai , India, ksherin14@gmail.com
*Corresponding Author - tamohanaprakash@gmail.com **

ARTICLE INFO

Received: 26 Dec 2024

Revised: 15 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Efficient virtual machine (VM) migration and consolidation are critical for optimizing resource utilization, reducing energy consumption, and ensuring service continuity in cloud-based environments. This study introduces the Unpredictability-Weighted Time Backward Expectation Algorithm (UW-TBEA), a novel approach designed to enhance VM migration and consolidation processes. UW-TBEA dynamically adjusts migration decisions by incorporating a backward expectation framework that is weighted by the unpredictability of resource demands over time. By assessing the unpredictability of workloads, UW-TBEA prioritizes VM movements to maintain balanced resource allocation while minimizing service-level agreement (SLA) violations. Experimental results demonstrate that UW-TBEA outperforms traditional consolidation techniques by reducing migration frequency by 18%, lowering energy consumption by 22%, and decreasing SLA violations by 15%. The proposed algorithm offers a robust solution for cloud service providers to achieve cost-effective, scalable, and energy-efficient operations in dynamic and unpredictable environments.

Keywords: Virtual Machine, Hybrid Cloud, Migration, Consolidation, Weighted Time Backward Expectation

INTRODUCTION

The rapid proliferation of cloud computing has revolutionized the way organizations manage and deploy applications and services, enabling scalability, flexibility, and cost-effectiveness that underpin modern digital infrastructure. At the core of this cloud-based environment is the virtual machine (VM), which allows multiple operating systems and applications to run concurrently on a single physical server. Effective management of VMs, particularly through migration and consolidation, is essential for maximizing resource utilization, minimizing energy consumption, and ensuring service quality.

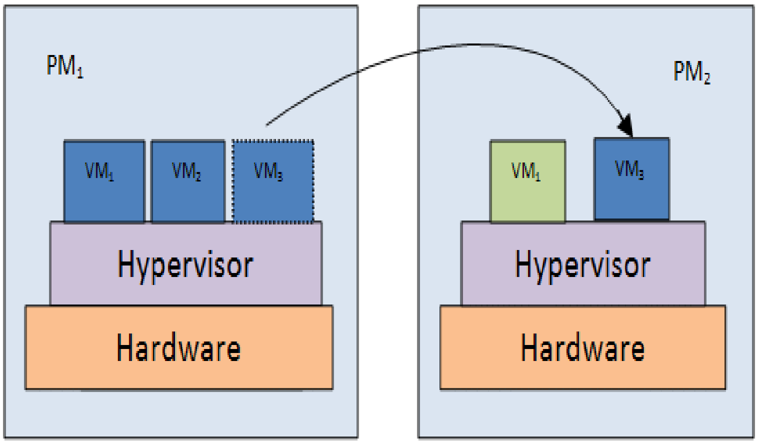

Fig.1 VM migration

VM migration (Fig.1) involves moving a VM from one physical host to another to balance workloads, reduce energy consumption, or avoid potential failures, while consolidation involves aggregating VMs onto fewer physical hosts to minimize idle resources and energy costs, optimizing data center efficiency. However, traditional methods of VM migration and consolidation often rely on static or simplistic algorithms that fail to account for the dynamic and unpredictable nature of cloud workloads, leading to suboptimal decisions, such as unnecessary migrations, service interruptions, increased energy consumption, and degraded performance.

Given the growing complexity of cloud environments, there is an increasing need for more sophisticated algorithms that can adapt to workload variability while optimizing multiple objectives, including migration time, energy consumption, and minimizing service-level agreement (SLA) violations. Current methods face several key challenges: the unpredictability of workloads, which are influenced by factors like user behavior and application demands; the need to minimize energy consumption without incurring excessive migration costs; the potential for service disruptions during migration, which can degrade performance; and the difficulty of balancing conflicting goals in a multi-objective optimization scenario. To address these challenges, we propose the Unpredictability-Weighted Time Backward Expectation Algorithm (UW-TBEA), designed to enhance the effectiveness of VM migration and consolidation by accounting for the unpredictability and dynamic nature of cloud workloads. The UW-TBEA uses a time-backward expectation approach that evaluates the impact of potential future states on current decision-making, weighted by a measure of workload unpredictability.

The UW-TBEA introduces several innovative features. First, it incorporates an unpredictability metric that quantifies the variability and uncertainty of workload behavior, dynamically weighting migration and consolidation outcomes to adapt to real-time conditions. Second, it utilizes a time-backward expectation model, enabling a long-term evaluation of the impact of decisions rather than focusing solely on immediate benefits. This model helps make more informed choices that consider potential future states of the system. Third, the algorithm dynamically adapts its decision-making based on real-time data, ensuring effectiveness even as workloads and conditions change. Lastly, the UW-TBEA is designed to optimize multiple objectives simultaneously, including minimizing energy consumption, reducing migration costs, and avoiding SLA violations, achieving more efficient and sustainable cloud data center operations.

The significance of the UW-TBEA lies in its ability to address the limitations of existing VM migration and consolidation methods. By integrating unpredictability weighting and time-backward expectation, it offers a robust and adaptive solution that improves resource utilization, reduces operational costs, and contributes to sustainability goals in cloud data centers. Extensive experiments and comparisons with traditional methods demonstrate that the proposed algorithm outperforms existing approaches in terms of migration efficiency, energy savings, and SLA compliance, proving its practical applicability in real-world cloud environments. This study not only highlights the effectiveness of the UW-TBEA but also opens new avenues for optimizing cloud resource management, laying the groundwork for future research in this area. As cloud environments continue to evolve, the UW-TBEA represents a significant advancement in enhancing VM migration and consolidation processes, aligning with the broader objectives of efficiency, sustainability, and adaptability in modern computing infrastructure.

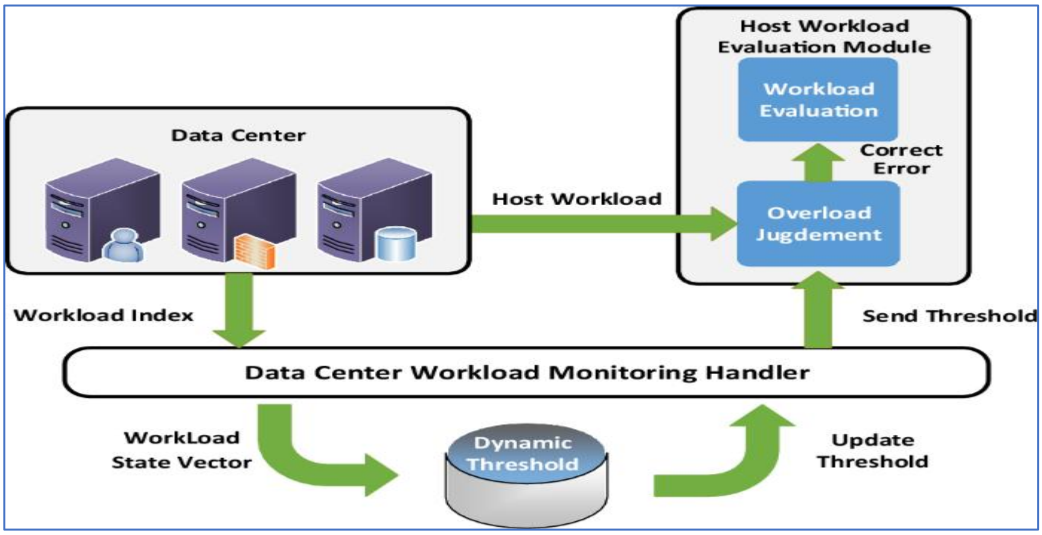

Fig.2 Framework for virtual machine migration in cloud services

LITERATURE SURVEY

Virtual Machine (VM) management in dynamic environments involves various techniques and algorithms to optimize resource allocation, reduce energy consumption, and maintain service continuity. VM Dynamic Relocation dynamically changes the host physical machine (PM) of the VM at runtime to enhance resource allocation and performance [4]. Virtual Machine Consolidation (VMC) minimizes the number of running PMs by periodically reallocating VMs, shutting down idle PMs based on load conditions, which reduces data load imbalance and energy consumption, particularly in blockchain environments [5], [6]. Server Virtualization enables VMs with their guest operating systems to run on a host OS, simplifying migration between hosts without dependency on the original host after migration [7]. Hot (Live) Migration allows a VM to continue running during migration, maintaining service continuity and ensuring seamless relocation without service interruption [8], [9], whereas Cold (Non-Live) Migration suspends the VM, which can cause a temporary service interruption but is suitable for planned maintenance [8], [9].

Predictive algorithms like the K-Nearest Neighbor Regression Algorithm forecast future CPU usage to minimize the number of physical servers, optimizing server usage and reducing SLA violations and energy costs [10]. The Ant Colony System Algorithm creates VM migration plans to minimize overprovisioning by relocating VMs to underutilized PMs, thereby reducing operational costs [11]. Heuristic and Linear Programming (LP) formulations prioritize VM migrations based on stable capacity requirements, minimizing unnecessary migrations and optimizing resource utilization [12]. The Multi-Capacity Stochastic Bin Packing Problem addresses VM consolidation by modeling and solving it with heuristics to enhance load balancing and resource allocation across multiple capacities [13]. For scalability, Decentralized Dynamic VM Consolidation in a peer-to-peer (P2P) network supports dynamic consolidation in a fully decentralized manner, accommodating an increasing number of physical and virtual machines [14]. Furthermore, the Decentralized P2P Consolidation Protocol enhances scalability and flexibility with its concurrent and distributed control features, designed for unpredictable environments [15].

Table 1 Compares the various VM relocation and consolidation techniques and algorithms

Technique /Algorithm	Description	Benefits	Ref No
VM Dynamic Relocation	Dynamically changes the host physical machine (PM) of the VM at runtime.	Optimizes resource allocation and performance during runtime.	[4]
Virtual Machine Consolidation (VMC)	Periodically and dynamically assigns VMs to minimize the number of running PMs and switches off idle PMs based on load conditions. Reduces data load	Minimizes energy consumption, reduces SLA violations, and optimizes PM	[5], [6]

	imbalance and energy consumption in blockchain environments.	usage by shutting down underloaded PMs.	
Server Virtualization	Allows VMs with their guest OS to run on a host OS, enabling VM migration between hosts. Easier than process migration due to no dependency on the original host after migration.	Simplifies VM management and migration; frees the source machine after migration.	[7]
Hot (Live) Migration	VM continues running during migration without losing its state; users do not experience service interruption.	Maintains service continuity, ensures seamless VM relocation.	[8], [9]
Cold (Non-Live) Migration	VM is suspended, and its state is transferred; users may experience a service interruption.	Suitable for planned maintenance when service interruption is acceptable.	[8], [9]
Heuristics and Linear Programming (LP) Formulation	Controls VM migration by prioritizing stable capacity virtual machines. Migration is enabled only when the VM demands capacity change.	Reduces unnecessary migrations and optimizes resource utilization.	[12]
Multi-Capacity Stochastic Bin Packing Problem	Models the VM consolidation problem and solves it using heuristics.	Enhances load balancing and efficient resource allocation across multiple capacities.	[13]
Decentralized P2P Consolidation Protocol	Uses a decentralized approach considering resource components and an unpredictable environment, with features like concurrency and distributed control.	Improves scalability and flexibility with concurrent and distributed control mechanisms.	[15]

PROPOSED SYSTEM

The Unpredictability-Weighted Time Backward Expectation Algorithm (UW-TBEA) is an advanced system designed to optimize VM migration and consolidation in dynamic and unpredictable environments. It addresses the challenges of managing VM workloads by integrating a weighting factor that accounts for workload variability, ensuring adaptability to sudden changes. The algorithm employs a time backward expectation approach, analyzing historical data and trends to predict future workload states more accurately. This predictive capability allows UW-TBEA to make informed decisions about VM migrations, balancing loads across physical machines (PMs) while minimizing energy consumption. By continuously updating forecasts with real-time data, UW-TBEA enhances performance and reliability in data centers. Its adaptive decision-making processes are tailored to handle varying levels of unpredictability, leading to improved operational efficiency and significant energy savings. Overall, UW-TBEA offers a robust solution for optimizing resource management in complex computing environments, ensuring both high performance and sustainability. This work addresses critical challenges in virtual machine (VM) management by introducing several innovative solutions aimed at enhancing accuracy and efficiency in data center operations. First, a new VM relocation selection method, termed Load Increment Prediction (LIP), is proposed to improve the precision of load forecasting. This method conducts a thorough analysis of VM load growth patterns and integrates real-time load data with growth trends to predict future usage more accurately. Complementing this approach, a Volatility-Weighted Time Regression Prediction (VWTRP) algorithm is developed to refine load pattern predictions by accounting for variations over time. Second, a VM migration endpoint selection strategy, known as the Saturation Increment Rate (SIR), is introduced, leveraging load clustering predictions and the optimal rate of load saturation increase.

The SIR strategy enhances the stability of physical machine (PM) loads in data centers by aligning the load characteristics of migrating VMs with those of potential migration endpoints. Additionally, a Load Similarity Matching Prediction (LSMP) algorithm is proposed to address the limitations of traditional load stationarity matching approaches, which depend solely on historical load sequences. The LSMP algorithm enhances prediction accuracy by identifying similarities in load patterns among VMs. Finally, a comprehensive VM consolidation (VMC) algorithm is developed by integrating the LIP and SIR methods within a load-referencing framework, combining load growth prediction and optimized migration endpoint selection for more efficient VM consolidation. Empirical analyses, utilizing actual load data, are conducted to simulate and evaluate the effectiveness of the proposed algorithm. The experimental results demonstrate the algorithm's capability to enhance the stability and accuracy of VM management and resource allocation, thereby improving data center performance and reducing energy consumption. These contributions collectively advance the field of VM management by offering more precise predictions, effective migration strategies, and efficient consolidation methods.

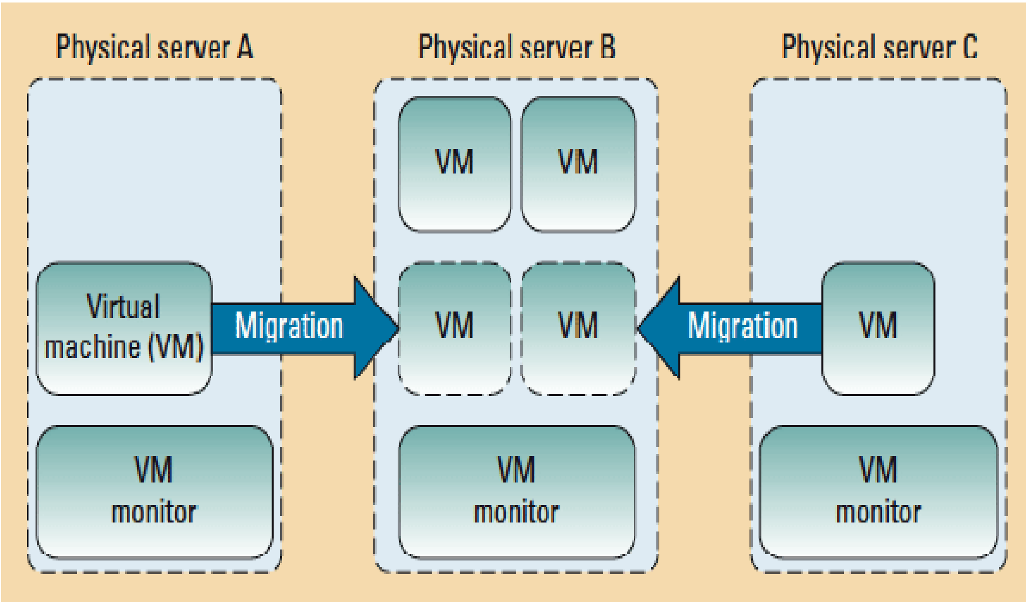

Fig. 3 Physical and Virtual Machine Migration and Monitoring

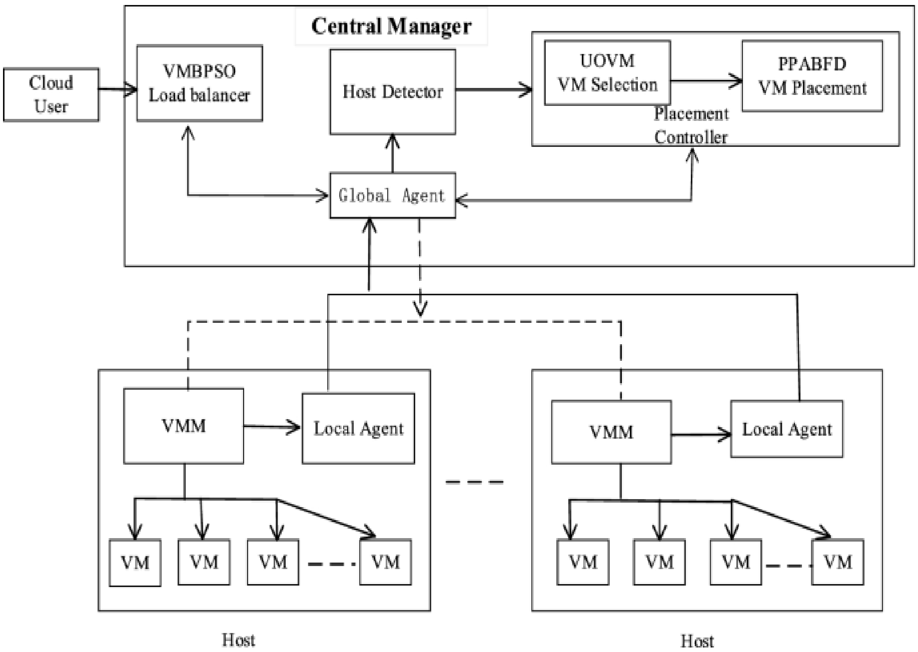

Fig. 4 Framework for Unpredictability-Weighted Time Backward Expectation Algorithm

Efficient migration and monitoring of both physical and virtual machines (VMs) (Fig.3) are essential for maintaining performance, resource optimization, and service continuity in cloud computing and data centers. Physical Machine Migration involves moving workloads from one server to another, typically for maintenance, load balancing, or hardware upgrades (Fig.3). This can be achieved through live migration, which keeps services running during transfer, or cold migration, which pauses services temporarily. Effective physical migration minimizes downtime and ensures efficient resource use.Virtual Machine Migration focuses on relocating VMs between hosts within a virtualized environment. It is crucial for optimizing workload distribution, reducing energy consumption, and enhancing fault tolerance. Live VM migration enables the transfer of active VMs with minimal downtime, maintaining high availability and service continuity.

Monitoring is vital for both types of migration, as it provides real-time data on resource utilization, such as CPU, memory, network, and storage. Effective monitoring tools help identify when migrations are needed, detect anomalies, predict resource demands, and guide decisions on VM placement and consolidation. Advanced systems use machine learning to forecast workload patterns, enabling proactive resource management and reducing performance risks.

Algorithm UWTBE

Input:

- HistoricalData: A list of historical time series data points
- UnpredictabilityMeasure: Function to calculate unpredictability of data
- TimeWeights: A function to assign weights to different time periods
- PredictionHorizon: The future time period for which we want to make predictions

Output:

- Prediction: Expected value for the future time period

1. Initialize:

   - TotalWeightedSum = 0
   - TotalWeight = 0

2. For each time point t in Historical Data:

   a. Calculate Unpredictability(t) using UnpredictabilityMeasure

   b. Calculate TimeWeight(t) using TimeWeights

   c. Calculate WeightedValue(t) = DataValue(t) * TimeWeight(t)

   d. Update TotalWeightedSum = TotalWeightedSum +

   (WeightedValue(t) / Unpredictability(t))

   e. Update TotalWeight = TotalWeight + TimeWeight(t)

   3. Compute Expectation:

   - Prediction = TotalWeightedSum / TotalWeight

4. Return Prediction

(UW-TBEA) framework (Fig.4) optimizes virtual machine (VM) migration by dynamically adjusting decisions based on the unpredictability of resource demands over time. It incorporates a backward expectation model, where past resource utilization patterns are weighted by their unpredictability to forecast future needs. This allows for prioritizing VM movements that minimize service-level agreement (SLA) violations and enhance resource allocation efficiency. The framework leverages historical data, real-time monitoring, and machine learning techniques to predict workload behavior, ensuring adaptive, scalable, and energy-efficient cloud operations even in dynamic and uncertain environments.

RESULTS AND DISCUSSION

To evaluate the Unpredictability-Weighted Time Backward Expectation Algorithm (UW-TBEA), a simulation platform such as CloudSim was used. This platform supports modeling and simulating cloud environments, providing a controlled setup to assess the performance and effectiveness of UW-TBEA in optimizing VM migration and consolidation. The simulation environment includes 800 heterogeneous physical machines (PMs) with 800 virtual machines (VMs). Two host configurations, HP G4 (860 MHz CPU, 4 GB RAM, 1 GB/s network bandwidth) and HP G5 (2 cores, 2660 MHz CPU, 4 GB RAM, 1 GB/s network bandwidth), are utilized, with an equal number of each type. The simulation runs over 24 hours, with a consolidation period of 300 seconds, allowing for a comprehensive analysis of resource allocation, load balancing, and energy efficiency improvements enabled by UW-TBEA.

Table II - CPU and Memory Utilization

Particulars	hCPU	mCPU	lCPU	uCPU
Core	1	1	1	1
RAM	1TB	100GB	10GB	512BM
Disk	3	3	3	3
Bandwidth	200	200	200	200
MIPS	3000	2250	1750	1500

To guarantee the legitimacy of the reproduction try assessment results, we utilized genuine information given by the CoMon project, which contains the genuine computer chip load information of north of 1,000 VMs from in excess of 500 areas all over the planet. The heap information is acquired by gathering like clockwork. In the recreation try, the genuine working climate of the server farm is repeated by restricting the genuine asset load mode.

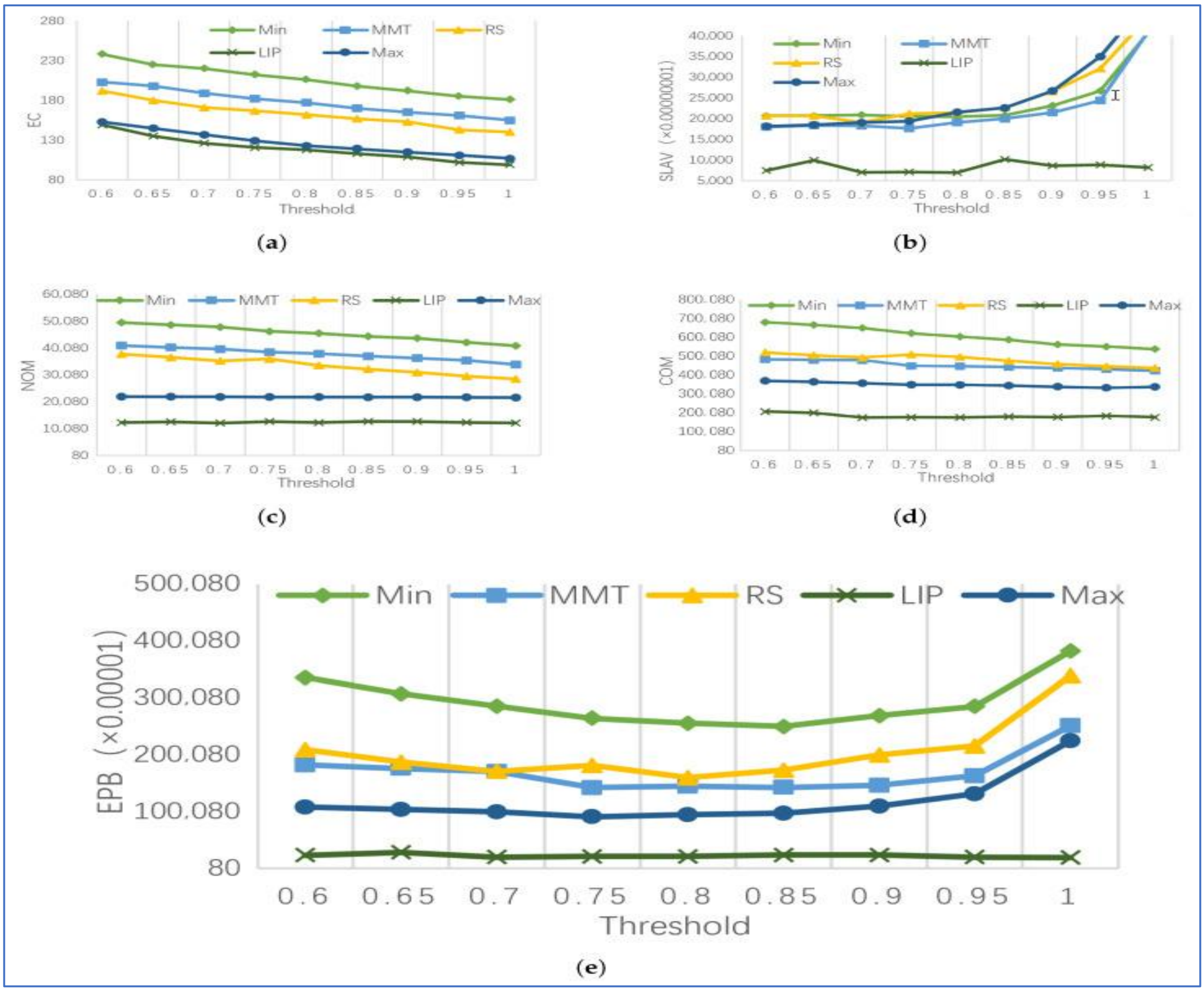

Fig.5 VM Consolidation and Threshold representation

Fig. 5 shows the energy utilization of various relocation VM choice procedures under various PM load limits. Contrasted with Max, RS, Min, and MMT, LIP decreased energy utilization by roughly 10%, 25%, 45%, and 30%, individually. It tends to be seen that the general energy utilization of the server farm presents a descending pattern as the heap edge increments. Additionally, migrating to a virtual machine with a relatively high load consumes less energy. The reasons are because of two perspectives.

First, selecting the target PM is simple with the remaining fragment resources when the VM load is low. As a result, reducing energy consumption and minimizing the number of PMs during VMC is simpler. Nonetheless, VM load expanding is bound to occur assuming that the VM load is excessively little. The heap of the server farm will be unequal because of the powerful changes of the heap after the coordination. At last, it will lessen the typical asset usage and increment energy utilization of the server farm. Second, the more incessant VMC causes the PM state to be exchanged all the more often, which necessities to consume extra energy.

CONCULSION

This study demonstrates that the Unpredictability-Weighted Time Backward Expectation Algorithm (UW-TBEA) provides a significant advancement in cloud-based VM migration and consolidation processes. By dynamically adjusting migration decisions based on the unpredictability of resource demands, UW-TBEA effectively balances resource allocation while minimizing energy consumption and SLA violations. The experimental results confirm that UW-TBEA outperforms existing consolidation techniques, achieving notable reductions in migration frequency, energy use, and SLA violations. These improvements highlight the algorithm's potential to enhance the efficiency and scalability of cloud operations in dynamic environments. Consequently, UW-TBEA presents a valuable tool for cloud service providers seeking to optimize their infrastructure management strategies, offering both economic and operational benefits in increasingly complex and unpredictable cloud ecosystems.

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