International Journal of Innovative Computer Science and IT Research

Volume 02, Issue 02 – Mar-Apr 2026 • E-ISSN: 3067-1108 | P-ISSN: 3067-1094

Intelligent Virtual Machine Scheduling for Optimized Cloud Resource Utilization

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Abstract

Cloud computing environments provide dynamically configurable computational resources that support applications with highly variable workloads. Virtual machines (VMs) are central to cloud resource management because they enable multiple applications and services to share physical infrastructure while maintaining logical isolation. However, inefficient VM scheduling can result in resource fragmentation, server underutilization, workload imbalance, unnecessary energy consumption, and degraded application performance. Intelligent VM scheduling addresses these limitations by incorporating workload characteristics, resource availability, historical utilization patterns, performance requirements, and predictive decision-making into scheduling processes. This paper examines intelligent virtual machine scheduling mechanisms for optimizing cloud resource utilization and develops a conceptual framework that integrates workload analysis, resource prediction, VM placement, dynamic rescheduling, and performance-aware decision-making. The proposed framework considers CPU, memory, storage, network capacity, workload intensity, VM priority, and energy consumption as interconnected scheduling factors. Particular emphasis is placed on adaptive scheduling strategies capable of responding to changing workload conditions and preventing resource hotspots.

The study analyzes traditional scheduling approaches alongside heuristic, metaheuristic, machine-learning-based, and reinforcement-learning-based mechanisms. The analysis indicates that intelligent scheduling can improve resource allocation by matching VM requirements with available infrastructure and dynamically adjusting placements as workloads evolve. Predictive mechanisms can further support proactive resource allocation by identifying upcoming demand changes before severe resource imbalance occurs. Nevertheless, intelligent scheduling introduces challenges involving computational overhead, prediction accuracy, scalability, heterogeneous infrastructure, migration costs, security, and quality-of-service requirements. The paper therefore proposes a balanced approach in which scheduling intelligence is applied according to workload complexity and resource-management requirements. The study concludes that future cloud platforms will increasingly require adaptive VM scheduling mechanisms capable of coordinating resource utilization, performance, energy efficiency, and service-level objectives.

Keywords: Virtual machine scheduling, cloud computing, intelligent scheduling, resource utilization, VM placement, workload prediction, cloud resource management, load balancing, virtualization, reinforcement learning

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Volume 02, Issue 02 – Mar-Apr 2026 ● E-ISSN: 3067-1108 | P-ISSN: 3067-1094

1. Introduction

Cloud computing has transformed the delivery of computational infrastructure by providing users with on-demand access to processing, storage, networking, and application services. Virtualization is one of the fundamental technologies supporting this model because it allows multiple virtual machines (VMs) to operate on shared physical infrastructure. Through virtualization, cloud providers can consolidate workloads and dynamically allocate infrastructure resources according to application requirements. However, the benefits of virtualization depend significantly on effective VM management. When virtual machines are scheduled inefficiently, physical servers may remain underutilized while others become overloaded, creating resource imbalance and reducing overall cloud efficiency.

VM scheduling determines how virtual machines are allocated to available physical hosts and how computational resources are distributed among competing workloads. Traditional scheduling approaches often rely on static policies such as first-fit, round-robin, priority-based allocation, or simple load balancing. Although these methods are computationally straightforward, they may perform poorly in highly dynamic cloud environments where workload demand changes continuously. Different applications may simultaneously require different combinations of CPU, memory, storage, and network capacity. Consequently, scheduling decisions must consider multidimensional resource requirements rather than focusing on a single resource metric.

Dynamic scheduling is particularly important for cloud environments supporting variable workloads. Web services, enterprise applications, data-processing tasks, and interactive platforms may experience rapid changes in demand. A static scheduling decision that is appropriate at one point may become inefficient as workload characteristics change. Intelligent schedulers can monitor resource utilization and modify VM placement when predefined thresholds or predicted demand changes indicate potential performance degradation. However, frequent migration can itself consume network bandwidth, processing capacity, and energy. Therefore, intelligent scheduling must account for the cost of changing an existing allocation.

The objective of this paper is to examine intelligent VM scheduling techniques for optimized cloud resource utilization and develop a conceptual framework for adaptive scheduling. The framework integrates workload characterization, resource monitoring, predictive analysis, VM placement, dynamic migration, and performance evaluation. It considers resource utilization as a multidimensional problem involving performance, energy, scalability, and quality of service. The study further discusses major challenges and future research directions for intelligent cloud schedulers capable of supporting increasingly heterogeneous and dynamic infrastructure environments.

2. Objectives

2.1 Primary Objective

The primary objective of this study is to examine intelligent virtual machine scheduling approaches that can optimize the utilization of cloud computing resources. The study focuses on adaptive allocation, workload-aware placement, resource balancing, predictive scheduling, and dynamic VM migration while maintaining application performance and quality-of-service requirements.

2.2 Development of an Intelligent VM Scheduling Framework

The study aims to develop a conceptual scheduling framework that connects workload characteristics with physical resource availability. The framework considers CPU, memory, storage, network capacity, VM priority, and current utilization levels when selecting suitable hosts for VM placement and rescheduling.

2.3 Integration of Predictive and Adaptive Mechanisms

Another objective is to investigate the role of machine learning, workload prediction, and adaptive optimization in VM scheduling. Predictive mechanisms can identify potential resource shortages and utilization changes, allowing scheduling decisions to be made proactively instead of waiting for performance degradation.

2.4 Optimization of Cloud Resource Utilization

The study also seeks to identify mechanisms for reducing resource fragmentation, preventing overloaded hosts, improving server utilization, and controlling unnecessary VM migrations. The objective is to achieve balanced resource utilization while maintaining acceptable performance, scalability, energy efficiency, and service quality.

3. Review of Literature

3.1 Virtualization and Cloud Resource Management

Virtualization provides the foundation for flexible cloud resource allocation by separating logical computing environments from physical hardware. It allows multiple VMs to share physical servers while enabling cloud platforms to dynamically manage workloads. Resource management therefore requires mechanisms capable of allocating infrastructure according to workload demand. Buyya et al. emphasized the importance of resource provisioning and scheduling in cloud computing environments, particularly because cloud workloads are dynamic and infrastructure resources are shared among multiple users.

VM scheduling is closely related to resource provisioning because placement decisions influence CPU utilization, memory availability, network performance, and energy consumption. Inefficient allocation can produce both overutilization and underutilization. Consequently, effective cloud schedulers must consider multiple resources simultaneously.

3.2 Heuristic and Optimization-Based VM Scheduling

Heuristic scheduling approaches provide relatively efficient solutions for complex VM-placement problems. Methods based on best-fit, first-fit decreasing, genetic algorithms, particle swarm optimization, ant colony optimization, and other metaheuristic techniques have been investigated for cloud resource allocation. These approaches attempt to identify high-quality placements without exhaustively examining every possible allocation.

The VM-placement problem is computationally difficult when cloud infrastructure contains large numbers of hosts and virtual machines. Optimization techniques can therefore provide practical solutions by balancing multiple objectives. However, metaheuristic approaches may require significant

Volume 02, Issue 02 – Mar-Apr 2026 • E-ISSN: 3067-1108 | P-ISSN: 3067-1094

computation and may not respond rapidly enough to highly dynamic workloads if their optimization process is too complex.

3.3 Machine Learning and Intelligent Scheduling

Machine learning introduces the possibility of predicting workload demand and identifying resource allocation patterns from historical data. Predictive models can estimate future CPU or memory utilization, detect potential hotspots, and support proactive VM placement. Reinforcement learning further enables scheduling agents to learn allocation policies through interactions with changing cloud environments.

Intelligent scheduling can therefore move beyond fixed rules toward adaptive decision-making. However, machine-learning-based schedulers require reliable training data, appropriate state representations, and careful control of inference overhead. Their effectiveness also depends on the ability to generalize across heterogeneous applications and changing infrastructure conditions.

4. Methodology

4.1 Research Design

This study adopts a conceptual and analytical research design to examine intelligent VM scheduling for cloud resource optimization. The methodology synthesizes established principles of virtualization, resource management, scheduling, workload prediction, and dynamic VM placement. Instead of presenting fabricated experimental results, the study develops a structured framework for analyzing how intelligent scheduling mechanisms can improve the utilization of heterogeneous cloud infrastructure.

The research considers VM requirements and physical-host characteristics as the primary scheduling dimensions. CPU capacity, memory availability, storage resources, network bandwidth, workload intensity, energy conditions, and VM priority are treated as relevant variables. Scheduling effectiveness is evaluated conceptually through resource utilization, load balance, migration overhead, responsiveness, scalability, and quality-of-service considerations.

4.2 Intelligent VM Scheduling Architecture

The proposed architecture contains five interconnected stages: resource monitoring, workload characterization, predictive analysis, scheduling decision-making, and dynamic resource adjustment. Monitoring mechanisms collect information about physical hosts and active VMs. Workload characterization identifies current and expected resource requirements. The predictive layer estimates future utilization patterns, while the scheduling engine selects appropriate VM-host mappings.

Dynamic resource adjustment enables the scheduler to respond when current allocations become inefficient. Depending on the detected condition, the system can migrate selected VMs, redistribute workloads, consolidate underutilized servers, or activate additional resources. The architecture therefore supports both proactive and reactive scheduling while attempting to control the overhead associated with frequent resource changes.

4.3 Key Scheduling Components

The methodology incorporates the following major components:

- **Resource monitoring:** Continuous observation of CPU, memory, storage, and network utilization.

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- **Workload characterization:** Classification of VM workloads according to resource requirements and behavior.
- **Demand prediction:** Estimation of future resource requirements using historical and real-time information.
- **Intelligent VM placement:** Selection of physical hosts according to multidimensional resource suitability.
- **Load balancing:** Distribution of VMs to reduce resource hotspots and imbalance.
- **Dynamic migration:** Relocation of VMs when existing placements become inefficient.
- **Resource consolidation:** Combining workloads where appropriate to reduce infrastructure fragmentation.
- **Performance evaluation:** Assessment of utilization, responsiveness, migration overhead, and service quality.

These components operate as an integrated scheduling cycle. Monitoring provides current-state information, prediction provides forward-looking information, and the scheduling engine combines both forms of information to select resource allocations. Dynamic adjustment then modifies the infrastructure configuration when required.

5. Analysis

5.1 Architecture of Intelligent VM Scheduling

Intelligent VM scheduling requires coordination between infrastructure monitoring, workload analysis, scheduling intelligence, and resource adjustment. A scheduler should not evaluate VM placement solely according to available CPU capacity because applications may have significantly different memory, storage, and network requirements.

Multidimensional resource awareness is therefore important for preventing resource fragmentation and host-level bottlenecks.

Table 1: Core Components of an Intelligent VM Scheduling Framework

Component	Main Function	Contribution to Resource Optimization
Resource Monitor	Collects host and VM utilization information	Provides real-time infrastructure awareness
Workload Analyzer	Identifies VM resource requirements	Supports workload-aware allocation
Prediction Engine	Estimates future demand	Enables proactive scheduling
Scheduling Engine	Selects VM-host mappings	Optimizes resource placement
Load Balancer	Distributes workloads across hosts	Reduces resource hotspots
Migration Manager	Controls VM relocation	Corrects inefficient allocations

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Component	Main Function	Contribution to Resource Optimization
Consolidation Module	Combines workloads when suitable	Reduces resource fragmentation
QoS Manager	Tracks service requirements	Protects application performance
Policy Controller	Defines scheduling priorities	Aligns allocation with operational objectives

Interpretation: The components presented in Table 1 demonstrate that intelligent VM scheduling is a continuous resource-management process. Monitoring and workload analysis provide the information required by the scheduling engine, while prediction enables proactive responses to changing demand.

Load balancing and migration address resource imbalance, whereas consolidation can improve utilization by reducing unnecessary fragmentation. The QoS manager ensures that resource optimization does not compromise application requirements. The interaction among these components allows scheduling decisions to consider both current infrastructure conditions and expected workload behavior.

5.2 Scheduling Mechanisms and Optimization Contributions

Different scheduling mechanisms address different resource-management problems. Static heuristics can provide rapid decisions for simple workloads, while optimization algorithms can consider multiple objectives.

Machine-learning approaches offer additional adaptability by learning workload patterns and identifying suitable resource configurations.

Table 2: Intelligent VM Scheduling Mechanisms for Cloud Resource Optimization

Scheduling Mechanism	Decision Principle	Primary Optimization Focus	Major Consideration
First-Fit/Best-Fit	Uses predefined placement rules	Rapid VM allocation	Limited adaptability
Priority-Based Scheduling	Allocates according to VM importance	Service differentiation	Priority conflicts
Heuristic Scheduling	Uses problem-specific rules	Fast resource optimization	May produce local solutions
Metaheuristic Optimization	Searches large solution spaces	Multi-resource placement	Computational overhead
Predictive Scheduling	Uses future demand estimates	Proactive allocation	Prediction accuracy

Scheduling Mechanism	Decision Principle	Primary Optimization Focus	Major Consideration
Reinforcement Learning	Learns scheduling policies	Adaptive resource allocation	Training complexity
Dynamic Load Balancing	Redistributes workloads	Host utilization balance	Migration overhead
Energy-Aware Scheduling	Includes energy conditions	Efficient infrastructure operation	Performance-energy trade-off

Interpretation: Table 2 shows that no single scheduling mechanism is universally optimal for every cloud environment. Rule-based methods are useful when rapid decisions are required, whereas heuristic and metaheuristic approaches provide greater optimization capability. Predictive and reinforcement-learning methods can respond more effectively to dynamic workloads but require additional computational resources and reliable state information.

Energy-aware scheduling introduces another dimension by considering infrastructure power consumption. Consequently, practical cloud schedulers may benefit from hybrid strategies that combine lightweight rules with intelligent prediction and adaptive optimization.

5.3 Factors Influencing Resource Utilization

Cloud resource utilization is affected by workload diversity, VM size, host capacity, application priority, and resource-demand variability. A physical host may have substantial available memory but insufficient CPU capacity, or the reverse. Such multidimensional imbalance can cause resource fragmentation even when aggregate infrastructure capacity appears sufficient. Intelligent schedulers must therefore evaluate resource dimensions jointly.

VM migration is another important factor.

Migration can correct inefficient placements and improve load distribution, but it requires computational and network resources. Excessive migration may create additional performance degradation and management overhead. The scheduler should therefore initiate migration only when the expected benefit is greater than the associated cost.

Workload predictability also influences scheduling strategy. Stable workloads can often be managed effectively using conventional allocation policies, whereas highly variable workloads benefit more from predictive and adaptive mechanisms. Similarly, latency-sensitive applications require rapid scheduling decisions, while batch-processing applications may tolerate more computationally intensive optimization.

6. Discussion

6.1 Intelligent Scheduling for Balanced Resource Allocation

Intelligent VM scheduling can improve cloud resource utilization by making allocation decisions according to multiple infrastructure and workload characteristics. Rather than assigning VMs based solely on immediate availability, an intelligent scheduler can examine resource compatibility, expected

demand, host utilization, and application requirements. This approach reduces the likelihood of placing workloads on unsuitable hosts and helps maintain a more balanced infrastructure environment.

Balanced allocation is particularly important in multi-tenant cloud platforms where different applications compete for shared resources. Scheduling mechanisms that recognize workload priorities can protect critical services while allocating remaining resources efficiently. Such policies can also reduce the frequency of emergency resource adjustments caused by unexpected host overload.

6.2 Predictive and Adaptive Scheduling

Predictive scheduling represents an important evolution from reactive resource management. By analyzing historical utilization patterns and recent workload behavior, predictive models can estimate future demand. The scheduler can then reserve or redistribute resources before utilization reaches critical levels. This proactive approach may reduce performance degradation and improve resource availability.

Reinforcement learning provides another adaptive mechanism in which scheduling policies evolve through interaction with the cloud environment. A learning agent can consider resource utilization, VM migration, service quality, and energy consumption when selecting actions. However, training and exploration must be carefully managed because inefficient decisions during learning can negatively affect production workloads.

6.3 Performance, Energy, and Quality of Service

Resource optimization should not be interpreted as maximizing utilization at any cost. Extremely high utilization may increase contention, latency, and application failures. Conversely, very low utilization may indicate inefficient infrastructure allocation. Intelligent scheduling should therefore seek an appropriate operating range that balances utilization with service quality.

Energy consumption is also increasingly important in cloud infrastructure. Consolidating VMs onto fewer servers can permit unused hosts to enter lower-power states, but excessive consolidation can produce hotspots. Intelligent scheduling should consequently evaluate energy, performance, and migration costs together. Multi-objective scheduling provides a promising direction for achieving balanced cloud resource management.

7. Challenges

One major challenge is the dynamic and heterogeneous nature of cloud infrastructure. Physical hosts may differ in processor architecture, memory capacity, accelerators, storage technologies, and network capabilities. At the same time, VMs may have highly different resource profiles. Designing a scheduling policy that performs consistently across heterogeneous environments requires accurate resource characterization and adaptable decision mechanisms.

Another challenge involves the overhead associated with intelligent scheduling. Machine-learning models, optimization algorithms, monitoring systems, and frequent scheduling decisions require computational resources. Excessive monitoring or model inference may reduce the benefits obtained through resource optimization. Similarly, frequent VM migration can consume network bandwidth and processing capacity. Intelligent schedulers therefore need mechanisms for controlling their own operational overhead.

Security and service-level requirements create additional complexity. Scheduling information may expose workload characteristics, infrastructure configurations, or tenant behavior. Furthermore, malicious or abnormal workloads may attempt to manipulate scheduling decisions by generating misleading resource patterns. Cloud schedulers must therefore incorporate appropriate security controls while preserving performance. Maintaining quality of service during dynamic resource allocation remains an equally important requirement.

8. Future Research

Future research should focus on lightweight predictive models that can provide accurate workload forecasts without introducing excessive computational overhead. Models should be capable of adapting to concept drift because application behavior may change over time. Federated and distributed learning approaches may also enable cloud infrastructure to share scheduling knowledge without centralizing sensitive workload information. Such mechanisms could support intelligent resource management across geographically distributed cloud environments.

Another important research direction is multi-objective intelligent scheduling. Future schedulers should simultaneously consider resource utilization, energy consumption, latency, migration cost, reliability, security, and service-level agreements. Instead of optimizing a single metric, adaptive scheduling algorithms could assign dynamic weights according to application requirements and infrastructure conditions. This approach would enable different scheduling policies to be selected for interactive, batch, real-time, and data-intensive workloads.

Future cloud platforms may also integrate VM scheduling with edge computing, serverless systems, containers, and specialized accelerators. This will create increasingly complex resource environments in which scheduling decisions must consider multiple execution models simultaneously. Digital twins and simulation-based scheduling could provide safe environments for evaluating scheduling policies before deployment. Combining predictive analytics, reinforcement learning, and simulation could ultimately produce autonomous cloud schedulers capable of continuously optimizing infrastructure resources with limited human intervention.

9. Conclusion

Intelligent virtual machine scheduling provides an important mechanism for optimizing resource utilization in dynamic cloud computing environments. Virtualization enables flexible resource sharing, but efficient utilization depends on the ability to allocate VMs according to workload requirements and infrastructure conditions. This paper examined an intelligent scheduling framework incorporating resource monitoring, workload characterization, demand prediction, VM placement, load balancing, dynamic migration, and resource consolidation. The analysis demonstrated that multidimensional resource awareness is essential because CPU, memory, storage, and network resources can become imbalanced independently. Intelligent scheduling can therefore help reduce resource fragmentation, prevent host overload, and improve the effective utilization of available infrastructure.

The study also examined heuristic, metaheuristic, predictive, reinforcement-learning, load-balancing, and energy-aware scheduling mechanisms. Each approach provides different benefits and introduces distinct limitations. Conventional heuristics can produce rapid allocation decisions, while optimization methods provide broader search capabilities. Predictive and learning-based approaches

offer greater adaptability for dynamic workloads but require reliable data, computational resources, and careful management of model complexity. Dynamic VM migration can correct inefficient placements, although excessive migration introduces additional network and processing costs. Consequently, intelligent scheduling should not optimize resource utilization independently of performance, energy consumption, migration overhead, and quality-of-service requirements.

Future cloud infrastructures will increasingly involve heterogeneous servers, specialized accelerators, edge resources, containers, and serverless execution environments. Such complexity will require scheduling mechanisms capable of making context-aware and adaptive decisions across multiple resource layers. Multi-objective optimization, lightweight machine learning, reinforcement learning, predictive analytics, and simulation-based scheduling represent promising directions for this evolution. The most effective future schedulers will likely be those that combine intelligence with operational efficiency, using sophisticated models only when their expected benefits justify their computational cost. By integrating adaptive resource allocation with performance and sustainability objectives, intelligent VM scheduling can contribute significantly to scalable, responsive, efficient, and resilient cloud computing infrastructures.

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