International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 2
Mar-Apr 2026, PP 01-20

A Critical Analysis of MCDM-Based Energy-Efficient Virtual Machine Consolidation in Cloud Data Centers: Challenges, Opportunities, and Future Research Directions

Dr. Vikas Mongia
Assistant Professor in Computer Science,
Guru Nanak College, Moga

Abstract. Cloud computing has become a fundamental technology for delivering scalable and on-demand computing resources. However, the rapid growth of cloud data centers has significantly increased energy consumption, operational costs, and carbon emissions. Virtual Machine (VM) consolidation is a widely adopted technique for improving resource utilization and reducing energy consumption by migrating VMs from underutilized servers and switching idle hosts into low-power states. Multi-Criteria Decision-Making (MCDM) techniques have emerged as effective approaches for VM consolidation because they can simultaneously consider multiple conflicting criteria such as CPU utilization, memory usage, network bandwidth, energy consumption, migration cost, and Quality of Service (QoS). This paper critically analyzes MCDM-based energy-efficient VM consolidation approaches, discusses their strengths and limitations, identifies current challenges, explores emerging opportunities, and highlights future research directions. The study reveals that while MCDM methods improve decision accuracy and energy efficiency, issues such as scalability, dynamic workload adaptation, uncertainty management, and integration with artificial intelligence remain significant research challenges.

Keywords: Cloud Computing, Virtual Machine Consolidation, Energy Efficiency, MCDM, Resource Allocation, Data Centers, Green Computing, QoS.

I. Introduction

Cloud computing has emerged as a dominant paradigm for delivering computing resources and services over the Internet through virtualization, resource pooling, and on-demand service provisioning. The rapid growth of cloud-based applications, big data analytics, artificial intelligence, and Internet of Things (IoT) services has significantly increased the deployment of large-scale cloud data centers worldwide [1]–[3]. These data centers host thousands of physical servers and virtual machines (VMs) to accommodate dynamic user demands while ensuring scalability, flexibility, and cost efficiency.

Despite their numerous advantages, cloud data centers consume substantial amounts of electrical energy, resulting in increased operational costs and environmental concerns. Energy consumption has become one of the most critical challenges in cloud computing because data centers require significant power not only for computing resources but also for cooling and supporting infrastructures [4]–[6]. Consequently, cloud service providers continuously seek energy-efficient resource management strategies that can reduce power consumption while maintaining Quality of Service (QoS) and Service Level Agreement (SLA) requirements.

Virtualization technology provides a fundamental mechanism for improving resource utilization by allowing multiple VMs to share the same physical infrastructure. Among various energy-saving techniques, Dynamic Virtual Machine Consolidation (DVMC) has emerged as one of the most effective approaches for reducing energy consumption in cloud data centers [5], [7]. The primary objective of DVMC is to consolidate workloads onto a smaller number of active physical machines through live migration of virtual machines, thereby enabling idle servers to be switched off or transitioned into low-power states. Numerous studies have demonstrated that effective VM consolidation can significantly reduce energy consumption while maintaining acceptable performance levels and SLA compliance [5], [8], [9].

A typical VM consolidation framework consists of four major decision-making stages: overload detection, underload detection, virtual machine selection, and virtual machine placement. Decisions made at each stage directly influence energy consumption, SLA violations, migration overhead, resource utilization, load balancing, and operational costs. Since these objectives are often conflicting, VM consolidation is inherently a multi-objective optimization problem that requires intelligent decision-making mechanisms capable of evaluating multiple criteria simultaneously [8]–[10].

To address these challenges, researchers have increasingly adopted Multi-Criteria Decision-Making (MCDM) techniques in cloud resource management. MCDM methods provide systematic frameworks for evaluating alternatives based on multiple and often conflicting criteria. Among these methods, the Analytic Hierarchy Process (AHP), proposed by Saaty [11], has gained significant attention because of its ability to decompose complex decision problems into hierarchical structures and derive criterion priorities through pairwise comparisons. AHP has been successfully applied to VM migration, VM selection, VM placement, and VM scheduling problems in cloud environments [12]–[16]. In addition to AHP, several other MCDM approaches, including Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Analytic Network Process (ANP), VIKOR, ELECTRE, PROMETHEE, MOORA, and fuzzy-based decision-making methods, have been employed to improve resource allocation and energy-efficient VM consolidation decisions [15], [17].

Although numerous MCDM-based solutions have been proposed for VM consolidation, existing studies remain fragmented and largely focus on specific consolidation stages or individual decision-making algorithms. Furthermore, many existing approaches rely on static criteria weights, assume independence among decision criteria, and fail to adequately address emerging challenges such as workload uncertainty, dynamic resource demands, carbon-aware computing, renewable-energy-powered data centers, edge-cloud integration, and intelligent predictive resource management [6], [18], [19]. Consequently, the applicability, strengths, and limitations of various MCDM techniques across different VM consolidation scenarios remain insufficiently explored. Several surveys have reviewed energy-efficient VM consolidation, cloud resource management, and VM placement strategies. However, a dedicated critical review focusing specifically on MCDM-based energy-efficient virtual machine consolidation is still lacking. Existing studies primarily emphasize algorithm development and performance evaluation while providing limited insights into the suitability, decision criteria, scalability, computational complexity, and practical applicability of different MCDM techniques. Furthermore, the strengths and weaknesses of existing MCDM approaches have not been systematically compared across the various stages of VM consolidation. Consequently, researchers and practitioners lack a comprehensive understanding of how different decision-making methodologies contribute to energy-efficient cloud resource management.

Motivated by these observations, this paper presents a comprehensive critical analysis of MCDM-based energy-efficient virtual machine consolidation techniques in cloud data centers. The study systematically reviews existing literature, develops a taxonomy of MCDM approaches used in VM consolidation, critically evaluates their strengths and limitations, and identifies emerging research opportunities involving predictive analytics, adaptive decision-making, explainable artificial intelligence, and carbon-aware cloud computing. Unlike conventional surveys, this work emphasizes the role of decision-making methodologies in achieving energy efficiency and sustainable cloud operations.

The main contributions of this paper are summarized as follows:

1. This paper presents a comprehensive and up-to-date review of Multi-Criteria Decision-Making (MCDM)-based approaches for energy-efficient virtual machine consolidation in cloud data centers, covering studies published across IEEE, ACM, Springer, Elsevier, Wiley, and PeerJ venues.
2. A systematic classification framework is developed to categorize existing MCDM approaches into weight-based, ranking-based, outranking-based, fuzzy-based, and hybrid decision-making frameworks.
3. The paper critically analyzes the decision criteria employed by existing approaches, including energy consumption, SLA violations, migration cost, resource utilization, load balancing, migration time, resource contention, bandwidth utilization, and carbon emissions. The strengths and limitations of various MCDM techniques are thoroughly discussed.
4. A comparative evaluation of widely adopted MCDM methods, including AHP, TOPSIS, ANP, VIKOR, ELECTRE, PROMETHEE, MOORA, and their hybrid variants, is conducted to assess their suitability for different VM consolidation scenarios.
5. Current research challenges, including criteria interdependency, static weight assignment, workload uncertainty, scalability issues, decision-making overhead, and dynamic cloud environments, are identified and critically examined.
6. Emerging research directions involving machine learning-assisted MCDM, predictive VM consolidation, adaptive weighting mechanisms, explainable decision-making, carbon-aware resource management, renewable-energy-aware consolidation, edge-cloud integration, and intelligent autonomous cloud management are highlighted to guide future research.

The remainder of this paper is organized as follows. Section 2 presents the review methodology and literature selection process. Section 3 discusses MCDM techniques used in energy-efficient virtual machine consolidation. Section 4 provides a critical analysis and comparative evaluation of existing approaches. Section 5 discusses open challenges and future research directions. Finally, Section 6 concludes the paper.

II. Review Methodology

This study adopts a systematic literature review (SLR) methodology to identify, analyze, and critically evaluate Multi-Criteria Decision-Making (MCDM)-based approaches for energy-efficient virtual machine consolidation in cloud data centers. Systematic literature reviews provide a structured and reproducible mechanism for synthesizing existing research evidence and have been widely adopted in software engineering and cloud computing studies [20], [21]. Furthermore, several recent surveys on energy-efficient cloud computing, resource management, and virtual machine placement have employed similar review methodologies to investigate research trends and identify future research opportunities [22]–[24].

Literature Search Strategy
The literature search was conducted using major scientific databases and digital libraries, including IEEE Xplore, ACM Digital Library, SpringerLink, Elsevier ScienceDirect, Wiley Online Library, and PeerJ. These databases were selected because they contain a substantial proportion of high-quality publications related to cloud computing, virtualization, resource management, and decision-support systems.

To ensure comprehensive coverage, combinations of keywords related to virtual machine consolidation, energy-efficient cloud computing, and MCDM techniques were used. The primary search terms included:

- “Virtual Machine Consolidation”
- “Energy-Efficient Cloud Computing”
- “Virtual Machine Placement”
- “Virtual Machine Migration”
- “Cloud Resource Management”
- “Multi-Criteria Decision Making”
- “Analytic Hierarchy Process (AHP)”
- “TOPSIS”
- “ANP”
- “VIKOR”
- “ELECTRE”
- “PROMETHEE”
- “MOORA”
- “Fuzzy MCDM”

In addition to keyword-based searches, backward and forward citation analysis was performed to identify influential studies and recently published works that may not have been captured through database searches alone.

Study Selection Criteria
To maintain the quality and relevance of the review, explicit inclusion and exclusion criteria were defined.

Studies were included if they:

1. Focused on cloud computing environments.

2. Addressed virtual machine consolidation, placement, migration, scheduling, or resource allocation.
3. Applied one or more MCDM techniques for decision-making.
4. Considered objectives such as energy efficiency, SLA management, resource utilization, migration cost, or load balancing.
5. Were published in peer-reviewed journals, conferences, or reputable digital libraries.

Studies were excluded if they:

1. Focused on non-cloud computing environments.
2. Did not employ decision-making methodologies.
3. Were duplicate publications.
4. Consisted only of abstracts, editorials, tutorials, theses, or non-peer-reviewed reports.
5. Lacked sufficient technical information for evaluation.

Data Extraction and Classification Framework

For each selected study, relevant information was systematically extracted, including publication year, venue, MCDM technique employed, cloud management objective, VM consolidation stage addressed, evaluation metrics, and reported outcomes. The extracted information was subsequently analyzed to identify research trends, commonly adopted decision criteria, strengths and limitations of existing approaches, and emerging research directions.

To facilitate a structured analysis, the selected studies were classified according to the underlying MCDM technique employed. The reviewed approaches were grouped into:

- Weight-based methods (e.g., AHP, ANP, Best-Worst Method)
- Ranking-based methods (e.g., TOPSIS, VIKOR, MOORA)
- Outranking methods (e.g., ELECTRE, PROMETHEE)
- Fuzzy MCDM approaches
- Hybrid MCDM frameworks

Furthermore, the studies were categorized according to the virtual machine consolidation stage they addressed, including overload detection, underload detection, virtual machine selection, virtual machine placement, and integrated consolidation frameworks. This classification forms the basis for the taxonomy and critical analysis presented in subsequent sections.

III. MCDM Techniques for Energy-Efficient Virtual Machine Consolidation

Virtual machine consolidation involves multiple conflicting objectives, including minimizing energy consumption, reducing SLA violations, limiting migration overhead, maximizing resource utilization, and maintaining load balance. Since no single criterion can adequately capture all consolidation requirements, researchers have increasingly adopted Multi-Criteria Decision-Making (MCDM) techniques to support migration and placement decisions. MCDM approaches enable the simultaneous evaluation of multiple decision criteria and provide systematic mechanisms for ranking alternative consolidation actions. Based on their underlying decision-making principles, MCDM techniques used in VM consolidation literature can be categorized into weight-based

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 2
Mar-Apr 2026, PP 01-20

methods, ranking-based methods, outranking methods, fuzzy MCDM approaches, and hybrid decision-making frameworks [25]–[30].

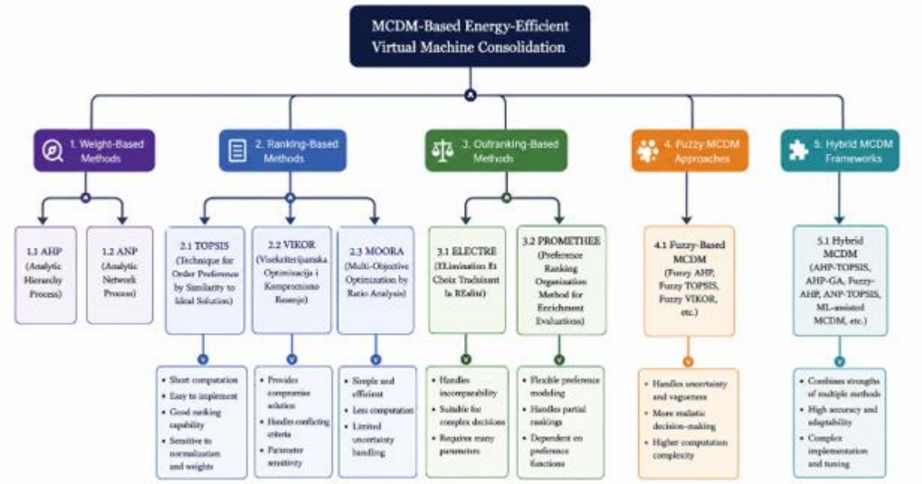

Figure 1. Taxonomy of MCDM Techniques Used in Energy-Efficient VM Consolidation

Weight-Based Methods

Weight-based MCDM techniques determine the relative importance of decision criteria before evaluating available alternatives. These methods are particularly useful in cloud environments where different resource management objectives have varying levels of significance.

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP), proposed by Saaty [11], is one of the most widely adopted MCDM techniques in cloud computing research. AHP decomposes a complex decision problem into a hierarchical structure consisting of objectives, criteria, sub-criteria, and alternatives. Through pairwise comparisons, decision makers assign relative importance to each criterion, and consistency analysis is performed to verify the reliability of judgments.

The popularity of AHP in VM consolidation research stems from its ability to simultaneously consider multiple resource management factors such as CPU utilization, memory utilization, energy consumption, migration cost, SLA violations, load balancing, and resource contention. Unlike traditional threshold-based consolidation approaches that rely on a single utilization metric, AHP enables a comprehensive evaluation of multiple performance indicators, resulting in more informed migration decisions [12]–[16].

Zhang et al. [12] presented one of the early applications of AHP in cloud environments by proposing an AHP-assisted virtual machine migration framework for green cloud computing. Sharma and Saini [13] subsequently utilized AHP for energy-efficient virtual machine consolidation by jointly evaluating energy consumption, migration cost, and SLA-related parameters. A significant advancement was reported by Ahmadi et al. [26], who proposed a flexible AHP-based virtual machine selection framework that simultaneously considered multiple resource utilization indicators and demonstrated improvements in energy efficiency and SLA compliance. More recently, Gu et al. [25] employed AHP in virtual machine scheduling decisions and reported improvements in resource allocation efficiency and overall scheduling effectiveness in cloud environments.

Researchers have also explored hybrid AHP frameworks to overcome the limitations of subjective weight assignment. Cao et al. [16] integrated AHP with optimization techniques to automate migration decisions, while Rehman et al. [27] incorporated multi-criteria evaluation into an energy-efficient VM consolidation framework to improve resource allocation decisions in cloud data centers.

Advantages: Simple implementation, transparent decision-making process, consistency checking, and support for qualitative and quantitative criteria.
Limitations: Assumes criteria independence, requires numerous pairwise comparisons, and often relies on static weights that may not adapt to dynamic cloud workloads.

Analytic Network Process (ANP)
The Analytic Network Process (ANP) extends AHP by modeling interdependencies and feedback relationships among decision criteria. Unlike AHP, which assumes hierarchical independence, ANP captures complex interactions among cloud resource management parameters such as CPU utilization, memory utilization, migration cost, and SLA violations. Consequently, ANP provides a more realistic representation of cloud decision-making environments [31]–[33].

Saaty [31] introduced ANP as a generalization of AHP capable of handling both inner and outer dependencies among decision criteria. Later, Chung and Seo [32] applied ANP to cloud service selection and demonstrated that cloud decision problems inherently involve feedback relationships among evaluation criteria. Similarly, Aragonés-Beltrán et al. [33] emphasized that ANP represents decision problems as interconnected networks rather than simple hierarchies, thereby improving decision quality in environments characterized by criterion interdependence.

Several researchers have explored ANP-based resource allocation and cloud scheduling frameworks to address criteria interdependency issues. ANP has demonstrated improved decision quality in situations where resource management metrics exhibit strong correlations and multiple conflicting objectives must be considered simultaneously [32], [33]. However, the increased number of pairwise comparisons and computational complexity often limit its adoption in large-scale cloud environments [31].

Advantages: Captures criteria interdependencies, provides realistic decision modeling, and improves decision accuracy.
Limitations: Higher computational overhead, increased complexity, and scalability challenges.

Ranking-Based Methods
Ranking-based MCDM techniques evaluate alternatives according to their relative closeness to optimal solutions. These methods are computationally efficient and have

been widely adopted for VM placement, resource allocation, and migration decisions in cloud environments [17], [34].

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)
TOPSIS ranks alternatives based on their distance from ideal and negative-ideal solutions. In cloud environments, TOPSIS has been applied to virtual machine placement, resource allocation, and load balancing decisions by simultaneously considering energy consumption, migration cost, SLA violations, and resource utilization [17], [34]–[36]. Hourali and Hourali [35] employed TOPSIS for VM placement and demonstrated reductions in energy consumption and the number of active physical machines. Alashaikh et al. [34] reviewed preference-based VM placement techniques and identified TOPSIS as one of the most widely adopted ranking methods because of its ability to evaluate alternatives according to their relative closeness to the ideal solution. Furthermore, Khorsand and Ramezanpour [36] integrated TOPSIS with multi-criteria weighting mechanisms to improve energy-efficient task scheduling in cloud environments.

Several studies have shown that TOPSIS-based placement strategies can improve both energy efficiency and SLA compliance compared with traditional threshold-based mechanisms [35], [36]. The technique has also been integrated with weighting methods such as BWM and AHP to further enhance decision quality in dynamic cloud infrastructures [36].

Advantages: Fast ranking mechanism, easy implementation, and suitability for large-scale decision problems.
Limitations: Sensitive to normalization methods and criterion weight assignment.

VIKOR
VIKOR focuses on identifying compromise solutions among conflicting decision criteria. In cloud resource management, VIKOR has been utilized to balance energy efficiency objectives with performance-related constraints. The technique seeks solutions that provide maximum group utility while minimizing individual regret, making it suitable for multi-objective VM consolidation problems [37], [38].

Jamali and Hourali [37] applied VIKOR-based VM placement and demonstrated improvements in migration cost, SLA satisfaction, and energy consumption. Similarly, Nayak and Tripathy [38] employed VIKOR as a decision-making mechanism for task scheduling and reported that the technique effectively resolves conflicts among competing alternatives while selecting compromise solutions.

The ability of VIKOR to generate compromise solutions has made it attractive for cloud environments characterized by competing optimization objectives. Consequently, several cloud resource management studies have adopted VIKOR to balance energy efficiency, service quality, and operational costs [37], [38].

Advantages: Effective compromise solution generation and support for conflicting objectives.
Limitations: Sensitive to parameter selection and ranking strategy.

MOORA

The Multi-Objective Optimization by Ratio Analysis (MOORA) method evaluates alternatives through ratio-based normalization and optimization procedures. MOORA has been adopted for VM placement and resource allocation decisions because of its simplicity and low computational complexity [39], [40].

Uma and Evangelin Geetha [39] integrated MOORA with the FUCOM weighting mechanism for cloud service provider selection and demonstrated reliable computation of criteria weights with simplified ranking procedures. Sindhu and Guruprasad [40] compared MOORA with TOPSIS and PROMETHEE in mobile cloud environments and reported that MOORA provides faster decision-making while maintaining acceptable ranking quality.

Researchers have reported that MOORA-based decision models can improve resource allocation efficiency while reducing computational overhead compared with several conventional MCDM techniques [39], [40]. Consequently, MOORA has emerged as a promising alternative for large-scale cloud decision-making environments.

Advantages: Low computational complexity, simplicity, and scalability.
Limitations: Performance depends on normalization strategy and criterion weighting.

Outranking Methods

Outranking techniques compare alternatives pairwise and determine whether one alternative dominates another under specific decision criteria. These approaches are particularly useful when decision criteria are conflicting and precise ranking becomes difficult [41], [42].

ELECTRE

ELECTRE employs concordance and discordance measures to establish outranking relationships among alternatives. Although less frequently used in VM consolidation than AHP or TOPSIS, ELECTRE has shown potential for complex cloud resource management scenarios involving multiple conflicting objectives and uncertainty [42].

Yazır et al. [42] compared ELECTRE III with other outranking-based decision-making techniques for cloud resource consolidation and demonstrated its capability to support multi-criteria resource management decisions. The ability of ELECTRE to evaluate alternatives under conflicting criteria makes it suitable for cloud environments where energy efficiency, performance, and migration overhead must be balanced simultaneously.

Advantages: Effective handling of conflicting criteria and partial preference relationships.
Limitations: Complex parameter tuning and computational overhead.

PROMETHEE

PROMETHEE utilizes preference functions to rank alternatives according to multiple evaluation criteria. The technique has been employed in cloud scheduling and resource allocation problems where decision transparency and ranking flexibility are required [41], [42].

Yazır et al. [41] proposed a PROMETHEE-based dynamic resource allocation framework for cloud environments and demonstrated improvements in autonomous resource management decisions. Subsequent studies further confirmed that PROMETHEE provides effective ranking capabilities for host selection and energy-aware resource allocation problems [42].

Advantages: Flexible preference modeling and intuitive ranking interpretation.
Limitations: Requires careful preference function selection and parameter tuning.

Fuzzy MCDM Approaches
Traditional MCDM techniques often assume precise decision information, whereas cloud environments frequently involve uncertainty and vagueness. To address this limitation, researchers have integrated fuzzy logic with MCDM techniques such as AHP, TOPSIS, ANP, and VIKOR [43]–[45].

Lee et al. [43] proposed a fuzzy MCDM framework for virtual machine resource reallocation and demonstrated its effectiveness in addressing uncertainty associated with cloud resource management decisions. Kumar et al. [44] combined Fuzzy-AHP and TOPSIS to improve cloud service ranking under uncertain environments. Similarly, Sun et al. [45] integrated fuzzy reasoning with ANP-based decision making and demonstrated improved cloud service selection performance under criteria interdependence and uncertainty.

Fuzzy MCDM approaches allow decision makers to represent uncertain judgments using linguistic variables and fuzzy numbers, thereby improving decision robustness under dynamic workload conditions. As a result, fuzzy decision-making frameworks have become increasingly popular for VM selection, host selection, resource allocation, and energy-aware scheduling problems [43]–[45].

Advantages: Handles uncertainty, ambiguity, and imprecise decision information effectively.
Limitations: Increased computational complexity and dependence on membership function design.

Hybrid MCDM Frameworks
Recent research increasingly focuses on hybrid decision-making frameworks that combine MCDM techniques with optimization algorithms, machine learning models, and predictive analytics. Hybrid approaches seek to overcome the limitations of standalone MCDM methods by improving adaptability, scalability, and decision accuracy [16], [28]–[30].

Unlike conventional MCDM approaches, hybrid frameworks exploit the complementary strengths of multiple techniques. For example, MCDM methods can be employed to determine the relative importance of decision criteria, while optimization algorithms are used to identify near-optimal consolidation decisions. Such integration enables cloud resource management systems to simultaneously address multiple objectives, including energy consumption, SLA violations, migration overhead, resource utilization, and load balancing.

Shi et al. [28] proposed a multi-objective resource allocation framework that improved resource utilization and workload distribution in cloud environments. Saxena et al. [29] developed a secure multi-objective virtual machine placement framework that jointly considers security, resource utilization, and energy efficiency. Similarly, Naji and Esmaeili [30] proposed an optimized VM placement approach for improving load balancing in cloud data centers. More recently, Gad-Elrab et al. [46] introduced an adaptive multi-criteria load-balancing framework for fog-cloud environments that dynamically adjusts resource allocation decisions according to changing workload characteristics.

Examples of hybrid decision-making frameworks include AHP-TOPSIS, Fuzzy-AHP, AHP-GA, AHP-PSO, ANP-TOPSIS, and machine-learning-assisted MCDM approaches. These frameworks have demonstrated promising results in reducing energy consumption, minimizing migration overhead, improving SLA compliance, and enhancing overall resource utilization [16], [28]–[30], [46].

Advantages: Improved decision accuracy, enhanced adaptability, better handling of multiple conflicting objectives, and superior optimization performance.
Limitations: Increased implementation complexity, higher computational overhead, and greater parameter tuning requirements.

Summary of Existing MCDM Approaches
The reviewed literature demonstrates that MCDM techniques provide effective mechanisms for addressing the multi-objective nature of virtual machine consolidation. Among the reviewed approaches, AHP remains the most widely adopted technique because of its simplicity, interpretability, and ability to incorporate both qualitative and quantitative decision criteria. TOPSIS and VIKOR are also frequently employed because of their computational efficiency and ranking capabilities. In contrast, ANP, ELECTRE, PROMETHEE, and MOORA have received comparatively limited attention in VM consolidation research despite their potential advantages in handling complex decision scenarios.

Recent studies indicate a growing shift toward fuzzy and hybrid MCDM frameworks that can better address workload uncertainty, dynamic resource demands, and conflicting optimization objectives. Furthermore, the integration of MCDM techniques with optimization algorithms, machine learning models, and predictive analytics has emerged as a promising research direction for next-generation cloud resource management systems.

Table 1 summarizes the major MCDM techniques used in energy-efficient virtual machine consolidation, their application domains, strengths, and limitations. The observations presented in this section provide the foundation for the critical analysis and comparative evaluation discussed in the next section.

Table 1. Summary of MCDM Techniques Used in Energy-Efficient VM Consolidation

Technique	Representative References	Application Area	Major Advantages	Major Limitations

AHP	[12]–[16], [25]–[27]	VM Selection, VM Scheduling	Simple, interpretable, consistency checking	Static weights, criteria independence assumption
ANP	[31]–[33]	Cloud Service Selection, Resource Allocation	Handles interdependent criteria	High computational complexity
TOPSIS	[17], [34]–[36]	VM Placement, Resource Allocation	Fast ranking, scalable	Sensitive to normalization and weights
VIKOR	[37], [38]	Task Scheduling, VM Placement	Compromise solution generation	Parameter sensitivity
MOORA	[39], [40]	Resource Allocation, Cloud Service Selection	Low computational complexity	Limited uncertainty handling
ELECTRE	[42]	Resource Consolidation	Handles conflicting criteria	Complex parameter tuning
PROMETHEE	[41], [42]	Resource Allocation, Scheduling	Flexible preference modeling	Preference function dependency
Fuzzy MCDM	[43]–[45]	VM Selection, Resource Allocation	Handles uncertainty and vagueness	Increased computational overhead
Hybrid MCDM	[16], [28]–[30], [46]	Integrated Resource Management	High accuracy and adaptability	Implementation complexity

IV. Critical Analysis and Comparative Evaluation

The increasing adoption of Multi-Criteria Decision-Making (MCDM) techniques in cloud resource management demonstrates the growing recognition that virtual machine consolidation is inherently a multi-objective optimization problem. Unlike traditional threshold-based approaches that primarily rely on CPU utilization, MCDM methods simultaneously consider multiple criteria, including energy consumption, SLA violations, migration cost, resource utilization, load balancing, migration overhead, and service performance. However, despite their effectiveness, existing MCDM approaches exhibit significant differences in terms of decision-making capability, computational complexity, scalability, uncertainty handling, and adaptability to dynamic cloud environments.

Comparative Analysis of MCDM Techniques

The reviewed literature indicates that no single MCDM technique is universally optimal for all VM consolidation scenarios. Each method possesses unique strengths and limitations that influence its suitability for different cloud resource management problems. AHP remains the most extensively adopted technique because of its simplicity, transparency, and consistency verification mechanism [12]–[16], [25]–[27]. The hierarchical structure of AHP facilitates intuitive decision-making and enables the incorporation of both qualitative and quantitative criteria. However, the technique assumes independence among criteria and relies on static weight assignments, limiting its effectiveness in highly dynamic cloud environments.

ANP addresses one of the major limitations of AHP by incorporating dependencies and feedback relationships among decision criteria [31]–[33]. This capability allows ANP to model realistic interactions among cloud resource management parameters such as CPU utilization, memory utilization, migration cost, and SLA violations. Nevertheless, the increased number of pairwise comparisons significantly increases computational complexity, thereby reducing scalability for large-scale cloud infrastructures.

TOPSIS has gained considerable attention because of its computational efficiency and ability to rank alternatives according to their proximity to ideal and negative-ideal solutions [17], [34]–[36]. The method is particularly suitable for VM placement decisions involving numerous candidate hosts. However, TOPSIS is highly sensitive to normalization procedures and criterion weight assignments, which may affect ranking stability. VIKOR differs from TOPSIS by focusing on compromise solutions among conflicting objectives [37], [38]. This characteristic makes it particularly suitable for balancing energy efficiency and SLA requirements. However, the quality of VIKOR decisions is strongly influenced by parameter selection and ranking strategies.

MOORA provides a computationally efficient alternative for multi-objective decision-making [39], [40]. The method is simple to implement and scales effectively in large cloud environments. Nevertheless, its ability to handle uncertainty and complex interdependencies among criteria remains limited.

ELECTRE and PROMETHEE belong to the outranking family of decision-making techniques and are particularly useful when alternatives cannot be easily ranked using conventional methods [41], [42]. These techniques effectively handle conflicting criteria and partial preference relationships. However, they require complex parameter tuning and are computationally more demanding than ranking-based methods.

Fuzzy MCDM approaches significantly improve decision quality under uncertain and dynamic cloud conditions by incorporating fuzzy logic into the decision-making process [43]–[45]. These methods allow decision makers to represent ambiguity and imprecise information using linguistic variables and fuzzy numbers. Although fuzzy approaches improve robustness, they often increase computational complexity and implementation difficulty.

Hybrid MCDM frameworks combine the strengths of multiple decision-making techniques and have emerged as one of the most promising research directions in energy-efficient VM consolidation [16], [28]–[30], [46]. By integrating MCDM methods with optimization algorithms, machine learning models, and predictive analytics, hybrid frameworks achieve improved adaptability, accuracy, and resource utilization. However, these benefits are accompanied by increased implementation complexity and higher computational overhead.

Comparative Evaluation of MCDM Techniques

Table 2 presents a comparative evaluation of the major MCDM techniques based on their suitability for energy-efficient VM consolidation.

Technique	Energy Efficiency	SLA Management	Scalability	Computational Complexity	Uncertainty Handling

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 2
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AHP	High	Medium	Medium	Low	Low
ANP	High	High	Low	High	Medium
TOPSIS	High	Medium	High	Low	Low
VIKOR	High	High	Medium	Medium	Low
MOORA	Medium	Medium	High	Low	Low
ELECTRE	Medium	Medium	Low	High	Medium
PROMETHEE	Medium	Medium	Medium	Medium	Medium
Fuzzy MCDM	High	High	Medium	High	High
Hybrid MCDM	Very High	Very High	High	High	High

The comparison reveals that hybrid MCDM frameworks generally provide the best overall performance because they combine multiple decision-making mechanisms and can adapt to dynamic cloud environments. In contrast, traditional techniques such as AHP and TOPSIS remain attractive because of their simplicity and lower computational requirements.

Analysis of Decision Criteria Used in VM Consolidation

A critical examination of the reviewed studies reveals that energy consumption remains the most frequently considered decision criterion, followed by SLA violations, resource utilization, migration cost, and load balancing. Most AHP- and TOPSIS-based approaches primarily focus on energy reduction and SLA compliance, whereas hybrid and fuzzy frameworks typically incorporate a broader set of evaluation criteria.

Despite the growing diversity of decision criteria, several important factors remain underexplored. Carbon emissions, renewable energy availability, thermal management, and environmental sustainability receive relatively limited attention in existing MCDM-based VM consolidation studies. Furthermore, few studies explicitly consider workload prediction uncertainty or the long-term impact of migration decisions on data center performance.

Research Gaps and Lessons Learned

The literature review highlights several important research gaps.

First, most existing approaches employ static criterion weights that remain unchanged regardless of workload variations. Such assumptions are unrealistic in cloud environments characterized by dynamic resource demands.

Second, many studies assume independence among decision criteria despite strong interactions among CPU utilization, memory utilization, migration cost, energy consumption, and SLA violations.

Third, most existing approaches remain reactive and make consolidation decisions only after resource utilization thresholds are exceeded. Predictive and proactive decision-making mechanisms remain relatively underexplored.

Fourth, although hybrid MCDM frameworks have demonstrated promising performance, their computational complexity often limits practical deployment in large-scale cloud infrastructures.

Finally, carbon-aware computing, renewable-energy integration, and edge-cloud resource management have received limited attention within the MCDM-based VM consolidation literature despite their growing importance in sustainable cloud computing.

These observations suggest that future research should focus on adaptive, predictive, explainable, and sustainability-aware decision-making frameworks capable of supporting next-generation cloud resource management systems.

V. Challenges and Future Research Directions

Despite significant progress in applying Multi-Criteria Decision-Making (MCDM) techniques to energy-efficient virtual machine consolidation, several research challenges remain unresolved. The increasing complexity of modern cloud infrastructures, coupled with dynamic workload characteristics and sustainability requirements, demands more intelligent, adaptive, and scalable decision-making mechanisms. This section discusses the major challenges identified from the literature and outlines promising future research directions.

Dynamic Weight Assignment and Criteria Adaptation
Most existing MCDM-based VM consolidation approaches employ static criterion weights that remain unchanged throughout system operation [12]–[16], [25]–[27]. In practice, however, the relative importance of decision criteria varies according to workload conditions, application requirements, resource availability, and service-level objectives. For example, energy efficiency may be the primary concern during low-utilization periods, whereas SLA compliance and performance may become more important during peak demand.

Future research should focus on adaptive weighting mechanisms capable of automatically adjusting criterion importance based on real-time system conditions. Machine learning, reinforcement learning, and context-aware decision-making techniques can potentially improve the responsiveness and effectiveness of MCDM-based consolidation frameworks.

Criteria Dependency and Complex Decision Relationships
Many existing studies assume that decision criteria are independent. However, cloud resource management parameters such as CPU utilization, memory utilization, network bandwidth consumption, migration cost, energy consumption, and SLA violations are often strongly interrelated [31]–[33]. Ignoring these relationships may lead to suboptimal consolidation decisions.

Although ANP and fuzzy-network-based approaches partially address this challenge, their computational complexity limits practical deployment. Future work should investigate efficient dependency-aware decision-making frameworks capable of modeling complex interactions without introducing excessive computational overhead.

Scalability in Large-Scale Cloud Data Centers
Modern cloud data centers may contain thousands of physical servers and tens of thousands of virtual machines. Under such conditions, the computational overhead associated with pairwise comparisons, ranking procedures, and optimization algorithms can become substantial [31]–[45].

Future MCDM frameworks should emphasize scalability by employing distributed decision-making mechanisms, parallel processing strategies, and lightweight evaluation techniques. Hierarchical and cluster-based consolidation frameworks may also improve decision efficiency in large-scale environments.

Workload Uncertainty and Predictive VM Consolidation
Most current VM consolidation techniques remain reactive, initiating migration decisions only after resource utilization thresholds have been exceeded. Such approaches often fail to anticipate workload fluctuations and may result in unnecessary migrations, increased SLA violations, and inefficient resource utilization.

Recent advances in machine learning and deep learning provide opportunities for predictive consolidation frameworks capable of forecasting future resource demands before performance degradation occurs. Future research should explore the integration of forecasting models, including LSTM, GRU, Transformer-based architectures, and reinforcement learning agents, with MCDM techniques to enable proactive decision making.

Carbon-Aware and Sustainable Cloud Computing
Existing MCDM-based consolidation studies primarily focus on reducing energy consumption and operational costs. However, energy efficiency alone does not necessarily guarantee environmental sustainability. Factors such as carbon emissions, renewable energy availability, cooling requirements, and regional electricity carbon intensity remain largely unexplored within current consolidation frameworks.

Future research should incorporate carbon-aware criteria into MCDM decision models and investigate green consolidation strategies that consider both energy efficiency and environmental impact. Such approaches can support the development of sustainable cloud infrastructures aligned with global carbon reduction objectives.

Edge–Cloud and Multi-Cloud Resource Management
The rapid growth of edge computing, Internet of Things (IoT), and multi-cloud environments has introduced new challenges for virtual machine consolidation. Unlike traditional centralized cloud infrastructures, edge-cloud systems are characterized by heterogeneous resources, geographical distribution, latency constraints, and limited computational capabilities.

Future MCDM frameworks should be extended to support distributed resource management across cloud, edge, and fog environments. Decision criteria such as network latency, user proximity, mobility patterns, and edge resource availability should be incorporated into next-generation consolidation models.

Explainable and AI-Assisted Decision Making
Artificial intelligence is increasingly being integrated into cloud resource management systems. Although AI-enhanced decision-making models often improve optimization performance, they frequently operate as black-box systems that provide limited explanation for their decisions.

Future research should investigate Explainable Artificial Intelligence (XAI)-based MCDM frameworks that can justify consolidation decisions in a transparent and interpretable manner. Combining explainability with MCDM techniques may improve trust, accountability, and practical adoption in enterprise cloud environments.

Autonomous and Self-Adaptive Resource Management
Future cloud infrastructures are expected to become increasingly autonomous. Self-adaptive resource management systems capable of continuously monitoring workloads, predicting future demands, adjusting decision criteria, and performing intelligent VM consolidation without human intervention represent a promising research direction.
The integration of MCDM techniques with reinforcement learning, digital twins, autonomic computing frameworks, and self-healing cloud architectures may facilitate the development of fully autonomous cloud resource management systems capable of achieving energy efficiency, SLA compliance, and sustainability objectives simultaneously.

In summary, future MCDM-based VM consolidation research should move beyond static decision-making models toward adaptive, predictive, explainable, sustainability-aware, and autonomous resource management frameworks. Addressing these challenges will play a crucial role in supporting next-generation cloud data centers characterized by increasing scale, complexity, and environmental responsibility.

VI. Conclusion

Energy-efficient virtual machine consolidation plays a crucial role in reducing power consumption, operational costs, and environmental impact in cloud data centers. However, VM consolidation is inherently a multi-objective decision-making problem that requires balancing several conflicting criteria, including energy consumption, SLA violations, migration overhead, resource utilization, and load balancing. Consequently, Multi-Criteria Decision-Making (MCDM) techniques have emerged as effective tools for supporting intelligent consolidation decisions.

This paper presented a comprehensive review and critical analysis of MCDM-based approaches for energy-efficient virtual machine consolidation. The study examined major categories of MCDM techniques, including AHP, ANP, TOPSIS, VIKOR, MOORA, ELECTRE, PROMETHEE, fuzzy MCDM approaches, and hybrid decision-making frameworks. The review revealed that AHP and TOPSIS remain the most widely adopted techniques because of their simplicity and computational efficiency, whereas ANP, MOORA, ELECTRE, and PROMETHEE have received comparatively limited attention in VM consolidation research.

The comparative analysis demonstrated that each MCDM technique offers unique strengths and limitations. Traditional methods provide transparent and interpretable decision-making, while fuzzy and hybrid frameworks improve decision quality under uncertainty and dynamic workload conditions. Recent studies increasingly integrate MCDM techniques with optimization algorithms, machine learning models, and predictive analytics to enhance consolidation performance and resource utilization.

The review also identified several research challenges, including static weight assignment, criteria interdependency, scalability limitations, workload uncertainty, and the lack of carbon-aware decision-making mechanisms. Furthermore, emerging computing paradigms such as edge computing, fog computing, and multi-cloud environments introduce new requirements that existing consolidation frameworks do not adequately address.

Future research should focus on adaptive and predictive MCDM frameworks capable of dynamically adjusting decision criteria according to workload conditions. The integration of artificial intelligence, explainable decision-making, workload forecasting, and sustainability-aware resource management represents a promising direction for next-generation cloud data centers.

In conclusion, MCDM techniques provide a powerful foundation for energy-efficient VM consolidation. However, future cloud environments will require intelligent, adaptive, and sustainability-driven decision-making frameworks that combine the strengths of MCDM methodologies with advances in artificial intelligence and autonomous resource management.

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