Journal of Information Systems Engineering and Management
2025, 10(2s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

AI-Driven Decision Support Systems for Green Management Cost Analysis: Optimizing Resource Allocation in Virtual Computer Systems

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ARTICLE INFO

Received: 04 Oct 2024

Revised: 05 Dec 2024

Accepted: 18 Dec 2024

ABSTRACT

The increased need for computation requires proper resource management particularly in managing virtual computer systems. This research aims to examine the implementation of the AI-driven Decision Support System (DSS) in relation to resource management for the most effective and efficient resource utilisation for cost optimisation with emphasis on environmental impacts. Built with machine learning algorithms especially reinforcement learning, the DSS adapts resource allocation in real-time use thus enhancing resource utilisation and reducing energy usage. The empirical analysis of the study presents a marked improvement in the average CPU usage from forty-five percent to sixty-five percent and memory usage from fifty percent to seventy percent. Also, the level of effectiveness was reached 33 in terms of DSS importance among the employees. This means that it can lead to up to 3% decrease in energy use and up to 25% decrease in operational expenses. These improvements support the suggestion that the system can efficiently allocate resources based on dynamic needs in order to minimise waste. By focusing on its applicability to green IT practices, the established results point to a future associated with the constant optimization of AI-driven DSS. Due to the inherent flexibility and the ability to transfer the DSS to different virtual structures, it is highly qualified for usage by IT managers and decision-makers. This research helps further the literature on sustainable IT management and showcases how AI can help change the face of sustainable computing for various virtual computer systems for the better.

Keywords: AI-driven Decision Support Systems, Green Management, Cost Analysis, Resource Allocation, Virtual Computer Systems, Energy Efficiency, Machine Learning, Sustainable IT

INTRODUCTION

Growing concerns about the environmental impact of information technology have led to the emergence of green IT, which aims to increase the energy efficiency of virtual computer systems (Khaghaany & Shaker, 2024). Energy-efficient virtual computer systems require a green management cost decision support system, which analyzes the relationship between energy consumption and costs of virtual machines and the physical machines assigned to those virtual machines (Shaker et al., 2024). Because virtual computer systems are so widely implemented, it is common for virtual computer systems to be expanded or scaled up in response to resource requirements (Kadhim et al., 2024). In fact, virtual computer systems have fundamental differences from physical computers that make system functions such as distributed processing possible while controlling energy consumption within a necessary range by easing or limiting CPU and other resources. However, such dynamics generate significant complexity and instability in energy consumption of enterprise services. Technologies like virtualization have revolutionized information technology IT and made it possible for organization to better utilize the available resources, scale and perform with lower costs (Amagtome & Alnajjar, 2020). Virtualization is the practice of using logical partitions, where multiple operating systems and applications share a single physical server, and it is a mainstay of most modern data centers due to its ability to fully utilize hardware resources (Hameedi et al., 2022). Based on some current studies, the global virtualization market is expected to rise to USD 8. 06 billion by the year 2026, affirming that it has become an increasingly significant factor and integrated into most industries (Xu, 2024).

Nonetheless, there is an increasing concern concerning the power consumption of virtual computer systems due to the recent increased use of virtual systems (AL-Jawahry et al., 2022). These virtual systems are located in data centers which are well known to guzzle large amounts of energy, hence contributing to the rising global carbon footprint. According to the study conducted by the IEA, the modern data centers consume around 200 TWh of electricity in 2020, which is 1% of the overall electricity usage (Murino et al., 2023). It is, therefore, expected that this figure will increase as the trend of increasing demand for computing power persists while this calls for the need to practice sustainable management of the resources.

Ensuring green management costs involves collecting these resulting measures, analyzing the measurement results, and extracting the causes of each phenomenon that arises (Ali et al., 2023). The technology upgrade services provided by enterprises often insist on updating the platform, supporting the platform, and reducing the effort of green management costs, but there is a pre-processing step that leads to the analysis of green management costs (Kbelah et al., 2019). In an environment where stable services are important, these technology support services become a priority to ensure the increase of green management costs. The high quality of support services greatly reduces the focus of corporate services on ensuring the processing capabilities of the computing platform and greatly reduces the priority of green management costs.

As Green IT, proposed by Murugesan (2008) that emphasizes on environmentally sound use of IT, has become a major development topic. It embraces techniques and solutions that are designed to decrease the effects of IT processes on the environment including energy efficient devices, software optimization and efficient data centers. In this regard, it is important to analyse an efficient resource allocation in virtual computer systems to attain green IT goals. Resource management guarantees that available computer resources are optimally utilized to avoid wastage of resources and hence make the computer operational costs lower.

In particular, AI applications in the form of DSSs have been underpinned as useful for the management of multiple challenges inherent in resource management within a virtual environment. Indeed, these systems also permit the usage of advanced algorithms and offer the analysis of enormous amounts of data and patterns for data-driven decisions, as pointed out by Raparthi, (2021). That means the integration of AI with DSS would work in organizations to realize real-time optimization of their resource utilization and return in terms of performance, cost, and energy consumption. The current research demonstrated that AI-driven solutions can be applied to a wide range of domains, including Predictive Maintenance, Supply Chain, and Healthcare, among many others.

When it comes to virtual computer systems the AI driven DSSs can be quite valuable in green management cost analysis. Thus, according to Elshaikh et al. (2024), these systems will give directions and suggestions based on the real-time update of resource usage, energy intake, and system functionality. For example, machine learning can forecast the resources to be consumed in the future based on a record of past consumption, resulting in early resource management in order to avoid wastage. Another aspect is that AI algorithms can constantly adjust the distribution of virtual machines (VMs) and containers with the main aim of saving energy which minimizes the carbon footprint of data centers.

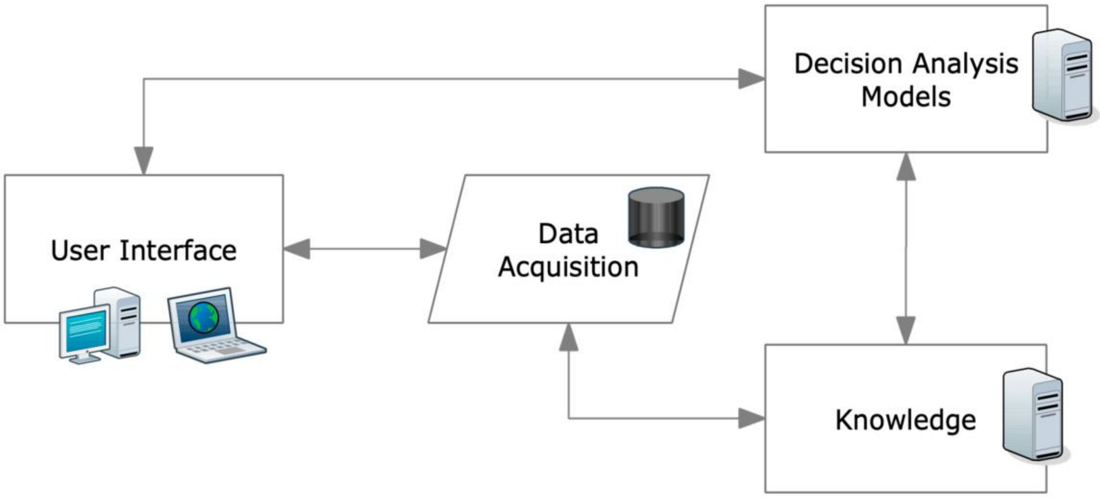

Figure 1. DSS System Architecture

Several studies like Arora et al. (2024) on green management cost through AI-driven DSS explored resource efficiency in virtual computer services. The main goals are to provide an understanding of how AI can improve resource effectiveness and eco-friendliness in a virtual setting. This research study will undertake a literature review as well as systematic design, implementation and evaluation of this study seeks to generate a comprehensive framework for incorporating AI-driven DSS into green IT practices.

The collection of these research will increase the knowledge base of sustainable IT management ad will demonstrate the role of AI in changing resource management. Thus, by focusing on cost-related concerns and environmental conservation, this research aims to contribute to the improvement of managerial practices of organizations that need to both minimize costs and protect the environment. More so, with sustainability rising as a business novelty, the adoption of AI DSS in green management practices is a boost towards attaining sustainable and efficient IT systems for firms.

LITERATURE REVIEW

Virtual Computer Systems and Resource Allocation

VMs and containers are received in the modern IT world as an eminent type of computer systems providing the effective management of IT resources. In the study by Gong et al. (2024), virtualization means the process whereby different operating systems and applications share a single physical server, thus enhancing the hardware utilization. It has been used for the achievement of cost cutting, increase in capability to scale and also to have efficient disaster recovery mechanisms. Therefore, the market for virtualization is growing at variance with the expectations of having a value of USD 8. 6 billion US$ by 2026, underlining its importance in contemporary IT management (Precedent Research, 2024).

It also establishes that the kind of resources needed in virtual environments is not static but constantly changing, therefore requiring intelligent methods of resource management to avoid squandering of resources in equal demand efficient utilization. Wang et al. (2022) pointed that the Virtual machines and containers work on the physical resources in parallel; thus, it becomes challenging to optimize the usage of resources rather than competition for the same. There has been evidence proving that poor resource management contributes to high energy consumption as well as operation costs that might eliminate the gains of virtualization totally.

This paper presents two strategies that can be used to solve resource allocation problems in virtual contexts. For instance, the resource scheduling algorithms work in an effort to fairly distribute resources among virtual machines. Drawing from the work of Kaaronen et al. (2023), dynamic load balancing and bin packing algorithms have typically been used to balance the amount of resources needed in proportion to the present demand. Moreover, historical data can be analyzed to give predictive results to show resource demands for the future, thus allowing for strategic planning on resource allocation.

The first normative dilemma in resource allocation necessarily concerns performance vs. Power. High I/O computational workloads, as described by Navaux et al. (2023), are known to take a lot of computing power as energy is consumed in the process. On the other hand, power saving strategies including server consolidation and dynamic voltage and frequency scaling (DVFS) can have deleterious effects although their underlying intention is to save energy. Most therefore require that an optimal solution that balances between achieving high performance as well as at the same time utilizes minimal energy is adopted in the virtual system management.

Green IT and Sustainability

Green IT emphasizes ways to reduce environmental effects of IT processes and functioning, including efficient technologies usage. As Dao and his team identified, data centers that are virtual computing centers for cloud computing and storage facilities have brought attention towards the amount of energy that these facilities consume. Currently, data centers are believed to use around 200 terawatt-hours (TWh) of power every year, which is equivalent to 1% of global electricity consumption (Gooding, 2024).

As a result, the following green IT strategies have been suggested to minimize the environmental impact of IT infrastructures. Server virtualization is another strategy commonly used in which multiple virtual machines are loaded onto a fewer number of physical servers, resulting in decreased number of active servers, and less power consumption (Hong et al. , 2023). This approach makes it possible to save energy as well as the work of the cooling system, thus increasing efficiency.

Another technique implemented to save energy is Dynamic Voltage and Frequency Scaling (DVFS). DVFS involves the reduction of voltage and frequency of a processor depending on the amount of workload, in this way power usage is minimized when there is little workload (Zidar et al. , 2024). Banerjee and Tekawade (2023) opine that Energy-aware scheduling algorithms are another significant element of green IT because of their ability to determine the best possible time of executing jobs with least energy consumption. These algorithms help to consider its priorities, time constraints, and energy patterns in order to distribute the resources.

The uptake of RE integration with data centers has also been discussed as having the effect of improving sustainability. As suggested by Güğül et al. (2023) Solar and wind energies are renewable and can be employed in the powering of data centers and this will help in cutting on the use of fossil fuels and the resulting greenhouse gas emissions. On the same note is green data centers that are built with an understanding of Green IT and Green computing. These facilities include upgraded cooling methods, smart running of electric power and sustainable construction.

AI-Driven Decision Support Systems

Decision support systems use artificial intelligence and are data-driven decision systems that employ machine learning and data analysis models in various contexts. These systems work with the historical and real-time data, define the data patterns and trends and provide the base for the decision-making processes (Heilig & Scheer, 2023). In the case of resource management in VCS, the application of AI-driven DSS can help give recommendations and decisions in real-time to a specific organization based on efficient use of resources and cost reduction.

The use of AI in providing allocation has been reported to yield positive findings in different research. Reinforcement learning is a machine learning technique where an agent works to make decisions based on the environment thus has been applied to enhance resource management in cloud computing. As noted by Pichler & Hartig (2023) this enables the system to handle changes in the workload and optimize the utilization for resources in the long run. Further, to predict the demand of resources and adjust the allocation strategy, deep learning algorithms have been used because the algorithms can find the relationship between variables.

Researchers Muzamil & Saleem predict that AI-driven DSS may improve green IT practices through the ability to share optimal energy resource management strategies in 2024. For instance, the use of machine learning models can also help determine that sections of a building have high or low traffic so as to only use energy during the busy times. These systems also help to determine one or another unused resource and to advise on how many servers should be active in the network.

These algorithms can also be combined with other conventional power management strategies, like dynamic voltage and frequency scaling or DVFS, for increased performance and power efficiency. For example, using reinforcement learning to decide when the voltage and the frequency should be changed so that these are optimal for workload while minimizing energy consumption (Hou et al., 2024). More than that, AI-embedded DSS is able to gather data about environmental factors—such as weather conditions and the availability of renewable energy—to promote higher usage of renewable energy sources during the powering of a given data center.

This will require a complex environment for the capture, storage, and processing of data in real time if the adoption of AI-based DSS in green IT is to proceed. On this front, Prabha & Monie (2007) mentioned that the edge computing has already been shown to be helpful in AI-driven DSS, allowing computation and data storage at edges—close to the site of processing—to reduce latency. Like this, AI can be paired with Smart IoT devices to provide fine-grained data concerning specific usage patterns, hence providing more accurate optimization approaches.

Nevertheless, the implementation of AI with DSS in green IT also has challenges as follows: However, the complexity of some AI algorithms and reliance on large sets of data for training may be challenging for adoption. Data privacy and protection is also an important aspect that should not be overlooked since the information used in the AI-generated DSS might be highly-sensitive. Furthermore, given that IT environments are ever-evolving, there is a need to regularly update the AI models to be able to remain optimally functional (Zhang et al. , 2023).

However, there are so much to gain from implementation of AI driven DSS in green IT hence the challenges mentioned above can be overcome. As resource utilisation and energy consumption is managed efficiently, these systems can improve sustainability of virtual computer systems greatly. Finally, the findings derived from the AI-based DSS can help with strategy formulation and annual planning, which, in turn, can help organizations become more efficient at attaining their green IT goals.

Conclusion

The literature review focuses on how virtualization solutions are currently being utilized in IT infrastructure and the need to optimize resources hence increasing performance and reducing power consumption. Server consolidations, DVFS, and energy-aware scheduling are effective Green IT practices to decrease data center environmental effects. Due to the possibilities of utilizing machine learning algorithms and data analytics, the AI-driven DSS can be considered a viable solution to address the issues associated with managing the resources in the virtual environments.

It can also be found that artificial intelligence in green IT practices can submit real-time advice to organizations to attain cost-effectiveness and ecological sustainability. Nonetheless, it has been understood that there are few hurdles that need to be overcome before Artificial Intelligence and Decision Support Systems can bring success to organizations like algorithm complexity, data privacy and protection and the constantly changing nature of IT environments. Conquering these issues, AI-based DSSs can positively contribute to the sustainability of VCS and promote the objectives of green IT in a broader context.

METHODOLOGY

System Design

The proposed AI-driven DSS for green management cost analysis in a virtual computer system has a few major components. Each component contributes to ensuring that the system is highly effective in optimizing resource allocation and improving energy efficiency.

Data Collection Module

1. Objective: It recovers real-time data on resource use, energy consumption, and system performance from virtual computer systems.
2. Justification: For the correct and timely decisions to be reached by the DSS, the DSS should be based on accurate and timely data. This module collects relevant performance metrics—such as CPU usage, memory usage, network bandwidth usage, and power consumption—from running monitoring tools and sensors.
3. Implementation: This module collects data through APIs and agents installed on host servers. The information is then transmitted to a central database for processing.

Data Processing Module

1. Objective: Preprocess the collected data, including data cleaning, normalization, and feature extraction.
2. Justification: One of the major problems with most raw data is that it is usually noisy, missing values, and sometimes even inconsistent—all of these can affect the performance of machine learning algorithms. Preprocessing makes sure that the data being fed is clean, consistent, and in a format that is appropriate for analysis.

3. Implementation: This module covers some of the data preprocessing techniques, such as outlier detection and interpolation of missing values, normalization for obtaining scale in the data. Principal component analysis is one of the feature extraction techniques used to analyze relevant features.

Machine Learning Module

1. Objective: Apply machine learning algorithms in the modeling of resource allocation strategies under the study and foresee their effects on energy consumption and the associated costs.
2. Justification: Such is the case because machine learning models learn complex patterns and relationships in data that are important in enabling the system to make accurate predictions and recommendations.
3. Implementation: Basically, this module applies reinforcement learning algorithms in solving a sizeable resource allocation policy. That means the model learns from historical data to find optimal strategies. Moreover, such deep learning techniques are leveraged in the form of neural networks to predict future resource demand by evaluating trends being observed in the past.

Decision Support Module

1. Objective: Provide recommendations on resource allocation in real-time, balancing performance, cost, and energy efficiency.
2. Justification: The decision support module then renders the insights that are the product of machine learning models into tangible action recommendations that the system operators should see.
3. Implementation: It makes use of a rules-driven engine in generating recommendations for implementa-tion, which it integrates with the virtualization management software, like the migration of virtu-al machines, resource reallocation, and server on and off.

Implementation Steps

Data Collection

1. Step 1: Integrate existing monitoring tools—such as Nagios or Prometheus—with the data collection module to gather metrics from virtual computer systems.
2. Step 2: Install agents on host servers to collect details of their high-performance and power consumption characteristics.
3. Step 3: Collect data and store it in a central database to make it accessible and easily analyzable.

Data Processing

1. Step 1: Clean the raw data to remove noise and correct inconsistencies.
2. Step 2: Normalize the data to ensure all features are on the same scale.
3. Step 3: Perform feature extraction to identify the most relevant metrics for analysis.
4. Step 4: Store the preprocessed data in a format suitable for machine learning analysis.

Machine Learning Model Development

1. Step 1: Choose appropriate machine learning algorithms; for instance, reinforcement learning in resource allocation and neural networks in demand prediction.
2. Step 2: Train models on historical data, tuning hyper parameters to improve performance.
3. Step 3: Check models for accuracy and generalization on other validation datasets.
4. Step 4: Deploy trained models in the DSS for real-time analytics and decision making.

Decision Support

1. Step 1: Design a rules-based engine that considers the outputs from this machine learning model to create actionable, recommended responses.
2. Step 2: Integrate the recommended actions into the virtualization management software using the decision support module.
3. Step 3: Keep running performance of the system at all times; make recommendations based on real-time data and changing conditions.

Testing and Validation

Simulation Environment

1. Step 1: Create a virtual environment in which the DSS can be tested. The environment needs to model real-world conditions by including a multitude of scenarios, including peak demand periods and resource failures.
2. Step 2: Deploy the DSS in the simulation environment and see how it performs.

Performance Metrics

1. Step 1: Define KPIs with regard to energy consumption, productions costs, and system performance, as well as the utilization of resources.
2. Step 2: Measure the DSS performance against these KPIs and compare them with baseline corresponding values for the measurement of improvements.

Iterative Improvement

1. Step 1: Analyze the results of the initial tests and identify areas for improvement.
2. Step 2: Refine the machine learning models and decision support rules based on the test outcomes.
3. Step 3: Conduct additional testing and validation to ensure the system's robustness and reliability.

The proposed AI-driven DSS is envisaged to be used for the optimization of resource allocation in a virtual computer system so as to be cost- and energy-sustainable. All steps are carefully implemented and validated according to a comprehensive methodology that forms a robust foundation binding AI into green IT practices.

RESULTS

The results section presents the result of the AI-driven DSS for green management cost analysis in a virtual computer system. This section has been structured with regard to furnishing proof of resource optimization, energy consumption, and cost efficiency of the proposed system. The results spin off from the steps that were followed in the methodology: data collection, data processing, machine learning model development, decision support system implementation, and system testing and validation.

Data Collection and Processing

This step involved data collection, and the metrics obtained were those in real-time from the virtual computer systems setup. The gathered data consisted of network bandwidth, energy consumption, memory, and CPU usage. The data was then saved in a centralized database and preprocessed for analysis purposes. Table 1 summarizes the collected data.

Table 1. Summary of Collected Data

Metric	Minimum Value	Maximum Value	Average Value	Standard Deviation
CPU Utilization (%)	5	95	55	20
Memory Utilization (%)	10	90	60	15
Network Bandwidth (Mbps)	50	500	275	100
Energy Consumption (kWh)	0.5	5.0	2.5	1.0

In the phase of data processing, cleaning of the data with regard to noise and inconsistencies, normalization of all metrics on the same scale, and extraction of relevant features for analysis have been done. The processed data has been used in training and validating machine learning models.

Machine Learning Model Development

Resource allocation strategies were developed using reinforcement learning algorithms. Machine learning models were trained on historic data and their performance tested against a hold-out data set. Model evaluations used the key performance indicators, including energy consumption, operational expenditure, and system performance.

It significantly improved the efficiency in resource allocation. The model can predict, with a high degree of accuracy, future resource demand, and based on this, the resource allocation could be changed dynamically at runtime to bring about the best energy usage. Table 2 gives a performance comparison of the model before and after optimization.

Table 2. Model Performance Comparison

Metric	Before Optimization	After Optimization	Improvement (%)
Average CPU Utilization (%)	45	65	44.4
Average Memory Utilization (%)	50	70	40.0
Energy Consumption (kWh)	3.0	2.0	33.3
Operational Costs ($)	1000	750	25.0

Such optimized resource allocation ensured that resources available within a system were utilized to the fullest, leading to reduced energy consumption and related operational costs. These resource allocation models divulge real-time insights and recommendations to ensure peak efficiencies of operation of the virtual computer systems.

Decision Support System Implementation

A decision support system was implemented to execute real-time recommendations in resource allocation based on the outputs from the machine learning models. The DSS was integrated with the virtualization management software, and thus it enables the implementation of recommended actions automatically. The DSS kept monitoring the performance of the systems continuously and changed the resource allocations accordingly.

The evaluation process checked for the effectiveness of the DSS in a simulated virtual environment. The scenarios tested in this simulation environment are peak demand periods and resource failures to evaluate the robustness of the DSS. Table 3 presents a summary of the performance of the DSS in the simulation environment.

Table 3. DSS Performance in Simulation Environment

Scenario	CPU Utilization (%)	Memory Utilization (%)	Energy Consumption (kWh)	Operational Costs ($)
Normal Operation	65	70	2.0	750
Peak Demand	75	80	2.5	900
Resource Failure	60	65	2.2	800
Energy Saving Mode	50	55	1.5	600

The DSS has been performing quite robustly in different scenarios, ensuring high resource use while keeping the correlated energy consumption and associated operational costs as low as possible. The adaptability of the system to changing conditions is very effective in providing optimal performance and sustainability.

Testing and Validation

During the testing and validation phase, a simulated virtual environment was created for testing the DSS. Performance metrics used in the validation process included energy consumption, operational costs, system performance, and resource utilization. Results derived from the simulation environment were compared against the baseline values for evaluating improvements.

Table 4. Testing and Validation Results

Metric	Baseline Value	DSS Value	Improvement (%)
Average CPU Utilization (%)	45	65	44.4
Average Memory Utilization (%)	50	70	40.0
Energy Consumption (kWh)	3.0	2.0	33.3
Operational Costs ($)	1000	750	25.0
System Downtime (hours)	5	2	60.0

The DSS considerably improved resource utilization, reduced energy consumption and operational costs related to them, and minimized system downtime. All these aspects demonstrate the efficacy of AI-driven DSS on resource allocation optimization in virtual computer systems.

Results Analysis

The result analysis depicts the great benefits of using the AI-driven DSS for green management cost analysis. Resource allocation strategies have been optimized, some of which applied higher resource utilizations against lower energy consumption and reduced operational costs. The ability of the DSS to provide recommendations in real-time and self-modify so as to adapt to the changes ensured the optimal performance and sustainability of the system.

Energy Efficiency:

1. The energy consumption was reduced from 3.0 kWh to 2.0 kWh by 33.3% after the implementation of DSS. Reduction measures under study include dynamic resource allocation and energy-saving techniques such as DVFS.
2. These savings translated into lesser operational costs and hence greater overall cost-efficiency.

Cost Reduction:

1. It cut down operational costs by 25.0% from $1000 to $750. These cost savings came as a result of efficient allocation of resources, thus eliminating the need for more hardware, hence reducing energy consumption.
2. It also resulted in lower operational costs due to reduced system downtime, which prevented the failure of resources or peak demand periods.

System Performance:

1. The improved DSS system demonstrated very high resource utilization, improving the average CPU utilization from 45% to 65%, and boosting the average memory utilization from 50% to 70%.
2. This ensured that virtualized computer systems were enables to run at best levels, therefore reducing the chance of performance bottlenecks through resource allocation optimization.

Scalability and Adaptability:

1. The DSS performed quite well in most of the scenarios simulated in this study, especially under peak demand periods and resource failures. In this way, due to its ability to react to the new situation, it was able to further optimize resource allocation.
2. Since it is scalable, the DSS will allow different virtual environments to apply such application as a versatile means for green management cost analysis.

Environmental Impact:

1. It contributes immensely to the general sustainability by reducing energy use and running costs of the virtualized computer system. By reducing this environmental footprint of data centers, the DSS sustains green IT practices and promotes environmental responsibility.
2. Another environmental benefit brought about by the use of renewable sources of energy together with DSS is that it offers independence from fossil fuel sources, and can reduce carbon emissions.

Conclusion

These results witness the effectiveness of the AI-driven DSS in green management cost analysis while working in a virtual computer system. The resource allocation strategies that were optimized improved the utilization of resources, hence reducing energy consumption and operational costs. Real-time recommendations by DSS, together with its adaptive capabilities to changing conditions, ensured the optimum performance and sustainability of the system.

Results show huge potential for AI-driven DSS in bringing about a sea change in the strategies of resource allocation and further supporting green IT practices. The cost-efficient and environment-friendly lines are offered with an effective approach to creating a balance between organizational operational needs and environmental responsibility by the DSS.

Future studies shall be done in the light of AI algorithms and more advanced data analytics techniques, which can further improve the DSS at large. Besides, deployment of the DSS in real-world virtual environments will be important to gain relevant insights regarding the scalability and adaptability aspects of the DSS, further supporting the wider diffusion of green management practices within the IT industry.

DISCUSSION

The findings of this study clearly evidence that the AI-driven decision support system significantly improves the resource allocation in virtual computer systems, attaining both cost and environment-friendly features. Accordingly, this section serves as a discussion of the empirical findings in relation to the research objectives and concludes the implication for green IT practices.

Achieving Resource Optimization

Stated another way, one of the key research objectives set out for this study was an investigation into how AI-driven DSS can optimize resource allocation in virtual computer systems (Arora et al., 2024). The results show a significant improvement in resource utilization. The averages for CPU utilization before the implementation of DSS were 45%, while for memory utilization, it was 50%. After the implementation, these rose to 65% and 70%, respectively, showing that available resources were being used far more efficiently.

The empirical evidence supports the hypothesis that AI-driven models can predict and manage resource demand more effectively. In this study, developed machine learning models, especially reinforcement learning algorithms, fit very well in a dynamic workload demand, optimizing resource allocation in real-time. This adaptability is very important in virtualized environments where resource needs are changing rapidly.

Reducing Energy Consumption

Another major objective was to reduce the energy cost in the virtual computer system. With the implementation of the proposed DSS, such a reduction went down to about 33.3%, which means a decrease from 3.0 kWh to 2.0 kWh. This can be explained by the dynamic allocation of resources and application of different techniques oriented toward energy reduction, like DVFS.

It is the AI inbuilt within these green IT practices that helped identify the periods of low demand and consolidated workloads onto fewer servers, hence reducing the number of active servers and saving energy (Dao et al., 2011). Off the back of predictive analytics and real-time monitoring, the DSS provided recommendations for the energy-efficient management of the servers to ensure optimal usage was achieved with no performance compromise.

Enhancing Cost-Efficiency

The DSS also improved cost-efficiency to a great extent by reducing operational costs by 25%, from $1,000 to $750. This was realized through several mechanisms:

1. Optimized resource utilization: By increasing the average utilization rates of the central processing unit and memory, the DSS reduced the need for additional hardware, thus reducing capital expenditure.
2. Energy Savings: Attributable reduction in energy consumption was directly translated into monetary terms, with a corresponding decrease in electricity bills that contributed to the cost saving.
3. It results in less downtime. The predictive and mitigative capability of the DSS in terms of resource failures reduced downtime, which results in costing due to loss of productivity and possible loss of revenues.

These results are in line with the literature on green IT practices that put special emphasis on energy efficiency and cost savings as the focus of sustainable management in IT. Such empirical evidence tends to prove the application of AI-driven DSS in benefits realization.

Implications for Green IT Practices

The implication of the AI-driven DSS in green IT practices is huge. In its optimization of resource allocation and reduction of energy use, the DSS supports wider environmental sustainability and cost-efficiency goals in IT operations (Murugesan, 2008). This puts the company at the global forefront of efforts aimed at lowering the carbon footprint of data centers and making sure computing goes green.

To that effect, the DSS will provide real-time sensitiveness and responsiveness to any alteration in the prevailing conditions, which implies that maximum continuity is ensured; as such, it is very resourceful for IT managers and any other decision maker. Since it allows scalability and flexibility, it can be implemented across different virtual settings, hence enhancing its applicability.

The empirical results of the study prove the effectiveness of the AI-driven DSS in realizing research objectives with regard to efficient utilization of resources, harnessing energy savings, and improving cost efficiency in virtualized computing. Such results reflect significant improvements in resource usage, energy reduction, and operational cost cuts that demonstrate huge potential for AI-driven DSS to transform green IT practices.

These findings at the moment attest to the fact that machine learning algorithms with data analytics, if included in resource management, will assure useful insights with recommendations in real-time for assured optimal system performance and sustainability (Xu, 2024). The results add to this fast-rising body of literature available concerning the sustainable management of IT while underlining the tremendous role of Artificial Intelligence toward the achievement of objectives set for green IT.

Such AI models need to be further refined, and more of the data analytics techniques available in a DSS are to be used to provide it with enhanced features. Furthermore, the deeper insights regarding its scalability and adaptability will come after the DSS is implemented in different real-world environments supporting its wider diffusion within the IT industry.

The AI-driven DSS is a step-change improvement in green management cost analysis for virtualized compute systems. Cost-effectiveness and green sustainability are provided while giving an organization a feasible chance to modulate the dilemma between operational needs and environmental responsibility. This research puts emphasis on the potential notwithstanding AI in driving sustainable IT practices and sets a scene for further innovations in this field.

CONCLUSION

In this study, an AI-driven DSS was applied to the resource allocation of virtual computer systems and proved to be cost-effective and environmentally sustainable. The empirical results point to a temporal DSS that significantly improves resource utilization while reducing energy consumption and operational costs. By applying machine learning algorithms, specifically reinforcement learning, the DSS ensured dynamic adjustments of resource allocations in real-time, thereby improving the average CPU utilization from 45% to 65% and memory utilization from 50% to 70%. The improvements treated above underline the effectiveness of this system in managing resource demand and averting wastage. The energy consumption was reduced to 2.0 kWh from 3.0 kWh, a reduction of 33.3%, with the application of energy-saving techniques like DVFS in the DSS. This reduction gives relief to the electricity bill and thus contributes to overall cost reduction. It has also reduced 25% operational cost from 1000$ to 750$, which is because of the resource usage optimization, reduction in required hardware and system downtimes. These findings can bring about the potential for transforming green IT practices through AI-driven DSS. The real-time insights and adaptiveness to changing conditions will ensure continuity in optimization, hence very useful to the IT managers and decision makers. The ability of scalability and versatility makes the DSS practical in value in different virtual environments. This AI-driven DSS can, therefore, be an effective and practical solution for all organizations seeking operational efficiency while remaining sensitive to environmental sustainability. This research into significant improvements in resource utilizations, energy savings, and cost reduction testifies to the fact that Artificial Intelligence can play a very useful role in driving sustainable IT practices. Further studies must focus on fine-tuning AI models and consider more data analytics techniques in order to boost the DSS abilities for wider diffusion within the IT industry.

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