

Original Article

Predictive Resource Planning For Energy-Efficient Cloud Computing and Enterprise Workload Management

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ABSTRACT

This paper proposes a conceptual framework for predictive resource planning in enterprise cloud computing to improve resource utilization, energy efficiency, and application performance. Traditional resource management approaches often fail to anticipate workload variations, leading to higher costs, resource wastage, and performance issues. The proposed framework integrates workload forecasting, energy-aware resource allocation, intelligent scheduling, and continuous performance monitoring using historical data and real-time system information. Its effectiveness will be evaluated using energy consumption, resource utilization, SLA compliance, prediction accuracy, response latency, and operational costs. The study provides a foundation for developing sustainable and intelligent cloud management systems, with empirical validation required to confirm its effectiveness.

KEYWORDS

Cloud Computing, Predictive Resource Planning, Energy-Efficient Computing, Workload Forecasting, Resource Allocation, Intelligent Scheduling, Enterprise Workload Management, Sustainable Data Centers.

1. INTRODUCTION

1.1. Research Background and Concept

Cloud computing is now a key part of how companies use technology today. Cloud computing lets companies get access to computer power, storage space, networking and other applications as they need them. Many companies are using public clouds (like Amazon Web Services), private clouds (like Open Stack), hybrid models (using both public and private clouds) and/or container technology to run some of their most important applications. Some examples of these types of applications include ERP systems, CRM systems, accounting systems, payment systems, data analysis tools, AI tools, and e-commerce platforms. Although there are many benefits to running applications in the cloud, managing the cloud itself is still a big technical problem. Cloud providers need to continually manage the trade-offs between application performance, resource availability, operating expenses, and energy usage. Business demands for computing resources change all day long and with each new business cycle. Also, different applications require varying amounts of processing power, memory, storage space, and network bandwidth. For example, a transaction-processing application will probably have consistent spikes in demand throughout the work day; however, an analytics application will probably have short-term high demand followed by long periods of low demand. To ensure that there is enough capacity for every potential spike in demand, cloud providers would need to provide excess capacity for long periods of time. On the other hand, if a cloud provider only provides enough capacity based upon average demand, then there could be times when there is not enough capacity to handle sudden increases in demand. Therefore, energy efficiency has emerged as a major factor in how cloud infrastructure is managed. Cloud data centres use energy for computing equipment, memory, storage, network devices, cooling systems and other support facilities. Not only does the energy used by computing resources depend on the total number of running servers; it also depends on the level of use of each server, the type of hardware used, whether the server supports power management features and how workloads are distributed across all available resources. Barroso and Hölzle (2007) highlighted the importance of energy-proportional computing and stated that computing systems must consume less power when they are performing fewer computations. Predictive resource management is an enhancement over traditional resource management. Predictive resource management uses historical workload data, recent telemetry data, and repetitive patterns of use, application dependencies and operational events to estimate future demand for resources. These estimates can help determine when to add additional capacity or move workloads to less utilized resources. The primary goal of this research was to show that predictive resource management should not view workload estimation as a separate analysis step. Workload estimates must be used to make actual resource allocation decisions, control energy-efficient infrastructure components, meet enterprise service requirements, and continually monitor resource usage. A highly accurate estimate of future resource demands will have minimal operational value if it does not lead to a decision about managing the resources needed to satisfy those demands.

1.2. Significance and Motivation



Fig 1 - Significance and Motivation

1.2.1. Energy Efficiency Improvement

Cloud data centers consume significant amounts of electrical energy to process enterprise workloads. Efficient resource planning helps reduce unnecessary power consumption and server energy waste. The proposed approach supports sustainable and energy-efficient cloud computing operations.

1.2.2. Optimal Resource Utilization

Traditional resource allocation methods may lead to underutilized or overloaded computing resources. Predictive planning allocates CPU, memory, and storage according to anticipated workload requirements. This improves resource utilization and reduces unnecessary infrastructure provisioning.

1.2.3. Workload Prediction and Management

Enterprise workloads frequently change according to business activities and user demand. Predictive analytics identifies workload patterns and estimates future computing requirements. Early prediction enables proactive resource allocation and better workload management.

1.2.4. Operational Cost Reduction

Excessive resource provisioning increases cloud infrastructure and electricity expenses. Intelligent resource allocation helps minimize unnecessary computing capacity and operational overhead. This approach can improve cost efficiency while maintaining required application performance.

1.2.5. Performance and Reliability Enhancement

Sudden workload increases can cause delays, resource shortages, and application performance degradation. Predictive resource planning helps prepare sufficient computing capacity

before demand peaks occur. This supports faster response times, improved service availability, and reliable enterprise operations.

1.2.6. Sustainable Enterprise Computing

Organizations increasingly require computing solutions that balance performance with environmental responsibility. Energy-aware workload scheduling helps reduce avoidable power consumption and improve infrastructure efficiency. The framework supports sustainable cloud operations and long-term enterprise resource management.

1.3. Research Problem and Objectives

The main research question is how to integrate future workload estimation, energy-efficient resource management and enterprise-wide service constraints into current resource management processes. While many existing approaches provide optimization for specific areas (i.e. utilization, energy), few address the potential impact of these optimizations on overall application performance and operational dependability. The primary contribution of this work is a conceptual model that links predictive intelligence with executing resource management actions. This model also explicitly addresses the requirement to meet service levels and maintain operational security.

2. LITERATURE SURVEY

2.1. Foundational Concepts and Existing Approaches

Cloud computing resource management includes allocating, scheduling, monitoring, and adjusting infrastructure resources to accommodate application needs. Buyya et al. (2009) introduced cloud computing as a utility-oriented computing model that had implications on architecture and economics. Their view demonstrated the need for resource allocation methods that could react to fluctuations in demand yet provide adequate service quality. Virtualization offers a fundamental base for flexible cloud resource management. It enables multiple virtual machines to run on the same physical hardware; thus, it supports workload isolation, resource consolidation, and dynamic placement. Container-based models build upon this support by providing lightweight application packaging and orchestration. However, even though virtualization and containerization offer many benefits regarding resource management, they do not guarantee energy efficiency. Unfavourable placement decisions, overly generous resource reservations, and inconsistent scaling strategies can lead to large amounts of unutilized capacity. Energy-aware resource management aims to decrease the amount of electricity used by data center infrastructures, while still maintaining the necessary levels of service quality. Beloglazov et al. (2012) reviewed various approaches to decreasing the energy consumption in data centers and cloud computing systems. They discussed how different aspects of energy management relate to scheduling and infrastructure usage, and that the area is not simply about reducing the amount of hardware used. Energy proportional computing is another related concept. Energy proportional computing is the idea that the power consumed by a system should match up better with the amount of work being done by the system. Barroso and Hölzle (2007) suggested that systems should try to limit the amount of electricity consumed when doing very little productive work. This idea supports the use of workload consolidation, better utilization of

servers, and managing idle infrastructure more effectively within an enterprise cloud environment. However, consolidating workloads depends on the compatibility of the workloads, what type of resource bottlenecks exist, and the availability requirements for each workload. There are many ways that resources are allocated in traditional resource allocation strategies. Some of those ways include statically allocating resources, reacting to threshold-based auto-scaling, allocating resources based on utilization, and reserving capacity based on policies. Statically allocating resources is easy to do, however, it can lead to inefficiency due to variability in demand. Auto-scaling, on the other hand, reacts to changes in utilization of resources. While auto-scaling works well for relatively stable workloads, it is limited by the time delay associated with monitoring intervals and scaling actions. Allocating resources based on utilization allows for better placement decisions because the current state of resource availability is taken into account; however, it does not allow for anticipating changes in demand early enough. Predictive planning adds a forward-thinking element to resource allocation. Resource consumption and workload characteristics are evaluated historically to predict future resource needs. Predictions can then be used to determine proactive scaling, workload migration, activating servers, and reserving capacity. Whether predictive planning will be successful will depend upon the accuracy of predictions, the timing of decisions, the availability of resources, and the capabilities of the orchestration system to perform predicted actions.

2.2. Recent Research and Technological Developments

Cloud simulation research and workload management research have laid down a solid base of knowledge for assessing different approaches to resource allocation. Calheiros et al. (2011) developed CloudSim, a software framework that allows for the creation of simulated cloud computing environments. Simulation is especially helpful when real-world testing is costly, disruptive to operations, or hard to replicate. Using simulation researchers are able to test various resource-allocation strategies in a controlled environment with specific workloads, however the simulation results are still dependent upon how realistically the simulated infrastructure and energy assumptions represent reality. Another major foundation is forecasting techniques. Time series forecasting methods are used to identify repeating workload patterns, trend lines, and temporal relationships. Machine learning forecasting methods can use additional variables such as application type, recent utilization, request volume, business calendars, and infrastructure events to help predict future workload demands. It should be noted that there is no one size fits all approach; a simple model can work well for relatively stable workloads whereas a more complex model may be better suited for workloads where demand is influenced by non-linear or diverse factors. Consequently, model selection should be backed up by time-aware validation and comparison to baseline models. Predictive accuracy must always be assessed relative to the specific decision being made, as emphasized in the general forecasting literature. Hyndman & Athanasopoulos (2021) highlight the significance of using suitable forecasting methods, analysing residuals, and assessing the performance of forecasts. A model that has an overall good performance may not necessarily perform well when trying to forecast rare demand spikes; thus, planning systems must take into account both the uncertainty of the forecast and what the operational implications are of underestimating demand. Resource orchestration is another area where workload management overlaps. Kubernetes has

several mechanisms that allow for scheduling workloads, specifying resource requests and limits, and scaling either horizontally or vertically. These mechanisms present practical opportunities for integrating predictive planning into Kubernetes; however, a forecasting component does not simply replace Kubernetes' existing scheduling logic or auto scaling logic. Rather, it can make suggestions or control capacity based on established orchestration rules.

Workload management in an enterprise also requires knowledge of application dependencies, priority of business, and availability goals. For example, if a resource-intensive analytics job is delayed or moved to protect a latency-sensitive transactional service; consolidation must consider maintenance windows, failure domains, and recovery capabilities. These examples show that energy-efficient planning must be viewed as constrained operational optimization and not merely reducing the number of active servers.

2.3. Research Gaps and Future Directions

Although there have been many advances made with respect to cloud orchestration and energy-aware scheduling, there are still some significant issues that need to be addressed. First, workload prediction and resource control have generally been considered to be two separate technical issues. Many times, prediction studies will state prediction error without evaluating if the error would significantly impact the ability to plan for capacity. Conversely, many scheduling studies make assumptions about the knowledge of future demands or create simplified workload profiles to represent future demands. An ideal evaluation would assess how well forecasting performance directly affects operational performance. Second, there are times when energy efficiency and service quality conflict. By consolidating workloads, we can reduce the number of active servers; however, increasing the utilization of a server may result in longer queue times and contention for CPU, memory, storage, or network resources. In addition, the configuration that is the most energy efficient at a given time may not provide enough resiliency to accommodate a future workload spike. Therefore, planning must include explicitly defined service constraints and a way to maintain reserve capacity. Third, the workload of enterprises is both heterogeneous (diverse) and non-stationary. The demand pattern could alter due to software releases, business events, seasonal transactions, data processing schedules, or unforeseen incidents. Therefore, models that have been developed using past data will be less accurate if there is a change in the aforementioned variables. It would then be relevant to monitor for model drift and regularly review model accuracy. Fourth, there are several practical implementation issues; such as telemetry quality, data governance, interoperability, and operational confidence. Performance metric data can come from various monitoring tools, but applications can define performance objectives differently. The predictive recommendations need to be explained well enough so that infrastructure personnel understand why capacity was added/removed/moved. Finally, there are many experimental environments that cannot accurately simulate the complexity of a production environment. Simulation of workloads typically simplify the interference between workloads, power consumption behaviours, networking costs and delays associated with orchestration. Consequently, future research should integrate reproducible simulation with carefully controlled experimental testing in a lab setting and, whenever possible,

privacy preserving evaluation of production environments. All of the above stated deficiencies provide rationale for the proposed integrated framework and validation process described below.

3. RESEARCH METHODOLOGY

3.1. Proposed Research Framework



Fig 2 - Proposed Research Framework

3.1.1. Workload Data Collection

Collects historical and real-time workload data from cloud computing environments. Monitors CPU utilization, memory usage, network traffic, and application demand. Integrates data from enterprise applications to understand resource utilization patterns.

3.1.2. Predictive Workload Analysis

Analyzes historical workload patterns to identify demand variations. Uses predictive analytics to forecast future resource requirements. Identifies peak workloads and potential resource shortages in advance.

3.1.3. Intelligent Resource Allocation

Allocates computing resources based on predicted workload demand. Adjusts CPU, memory, and virtual machine capacity dynamically. Prevents over-provisioning and under-provisioning of cloud resources.

3.1.4. Energy-Efficient Optimization

Reduces unnecessary energy consumption by optimizing server utilization. Identifies idle resources and supports efficient resource consolidation. Balances energy efficiency with application performance and service quality.

3.1.5. Performance Monitoring and Evaluation

Continuously monitors resource utilization, response time, and energy consumption. Compares performance against predefined efficiency and service-level objectives. Uses evaluation results to improve future workload predictions and resource allocation decisions.

3.2. Data Collection and Research Design

The study employs a systematic, conceptual research approach based upon a review of existing literature. It identifies common technical aspects and unresolved integration issues through an examination of relevant scholarly work regarding cloud computing; energy-efficient management of infrastructure; forecasting; and cloud simulation. Based on the common technical principles identified in the literature, the proposed architecture is designed to meet the operational needs of enterprise workload management. Literature sources used in this study include peer-reviewed journal articles, well-established conference proceedings, fundamental research papers, and credible technical documents, as applicable. Relevant literature sources are defined as those that relate to at least one of the following areas: cloud resource allocation, energy efficiency in data centres, workload prediction, auto scaling, cloud simulation, and infrastructure orchestration. The conceptual synthesis focuses on technical applicability, methodological clarity, and alignment with the research objective(s). This study does not claim to have created a new production dataset, an experimental test-bed, or a measurement of energy consumption. Therefore, the paper does not present empirical data, nor does it quantify performance enhancements resulting from implementation. The proposed framework and evaluation plan represent proposals for future verification, rather than representations that a previously implemented system demonstrates a specific degree of efficiency. Future empirical studies will require workload traces that represent different types of applications, as well as routine and maximum operating periods. Potential sources for these workload traces include public cloud workload traces, repeatable synthetic workload generator programs, and measurements obtained from a controlled business-type test environment. All data used must have adequate temporal resolution so it can accurately illustrate delays caused by scaling up/down, and burst-like workloads. In cases where there are no direct energy measurements available, all estimated power values should be clearly identified as being distinct from those directly measured, and calibrated using appropriate hardware or infrastructure specification(s). All data preparation must deal with missing observation points, unevenly sampled intervals, anomalous telemetry signals, and alterations in how the workload is defined. The training and evaluating data must be separated chronologically so no future information is leaked into the forecasting process. Validation strategies must include numerous workload regimes instead of only using one representative interval.

3.3. Evaluation Metrics and Comparative Analysis

The assessment framework includes forecasting quality, energy efficiency, resource usage, service reliability and operating expenses. These areas need to be evaluated as a single solution that decreases energy usage but increases service disruptions would not provide a viable enterprise solution. To determine how well a forecast performs, you will want to compare what you predicted would happen with what actually happened. You can assess how accurately you predicted continuous demand using either Mean Absolute Error (MAE) or Root Mean Square Error (RMSE). If you are looking at different workloads and their levels of use vary, then Scale Aware Metrics may assist in comparing those workloads. When evaluating a workload where there are numerous zero or close to zero observations, do not utilize percentage based error measurements as they become unreliable near zero. You can evaluate the energy efficiency of your infrastructure based on either

measured or properly calibrated infrastructure energy consumption during the same workload time frame. You will want to report both the total amount of energy consumed and the total amount of workload completed along with service performance and the boundaries used to measure the energy consumed. If you exclude facility cooling and power distribution overhead, then identify the measurement reported as "Server Level Energy" or "IT Level Energy" instead of "Total Facility Energy". The assessment of resources utilized will include CPU and Memory Utilization, Allocation to Usage Ratios, Number of Active Servers, and Duration of Unutilized Capacity. These indicators will assist in explaining if the changes in energy consumption are due to increased consolidation, decreased workload, etc. Performance of the Service will be assessed via Response Time Distribution, Throughput, Queue Delay, Failed Requests and violations to Service Level Agreement. While average latency can mask a large delay experienced by a very small fraction of requests in latency sensitive applications, average latency alone is not sufficient to evaluate latency in such applications. Cost of operation will include charges for infrastructure usage, reserved capacity, overhead for scaling and if quantifiable, costs related to migration or additional orchestration activities. Cost and Energy Results should be reported independently prior to interpreting them together as either a sustainable solution or economic outcome. Static provisioned baseline, reactive thresholds auto-scale baseline, utilization-aware scheduled baseline and the proposed predictive energy-aware approach should all be compared. All baselines should have identical workload input and similar service constraints. Sensitivity analysis will also be conducted for forecast error, scaling delay, energy assumption and reserve capacity policies.

3.4. Analytical Framework

An analytical framework for resource planning does not need a new mathematical equation to explain how it works. Resource planning is a sequence of constrained steps that include forecasting, decision-making, executing plans, and verifying outcomes. In this sequence, forecasting provides an estimate of what the future demand will be for each workload and resource type. Planning is the step where we determine whether the existing infrastructure can handle the estimated demand with adequate safety margin (headroom) to account for uncertainties and priority applications. Scheduling is the final step in the sequence where we make decisions about where to place and consolidate resources based upon factors such as resource compatibility, migration overhead, fault tolerance, and energy characteristics. There are four principles used in making decisions in the resource planning process. Principle 1: We must convert our estimated demand into usable capacity requirements, not just make a prediction about future demand. Principle 2: Energy-saving measures must not negatively affect application performance or availability. Principle 3: Uncertainty must play a role in making plans for resources, especially when the consequences of underestimating capacity are large. Principle 4: Every significant change made to the physical infrastructure should be evaluated based on actual results to help us correct any faulty assumptions we had when we planned the change. The proposed implementation of this methodology in the future could utilize a forecasting model to predict CPU usage and request levels; a policy engine to determine the necessary amount of extra capacity; and an orchestrator to apply requested scaling or placement decisions. In addition to these components, an energy component would assess the various possible courses of action based upon

hardware power usage characteristics (profiles) or actual consumption measurements; and a service governance component would prohibit actions that do not comply with application specific policies. Therefore, the analytical framework emphasizes consistent decision making and operational verification above all else, including excessive model complexity. This approach supports statistical forecasting, machine learning-based prediction, or hybrid approaches to forecasting, and does not require that all workloads within the organization utilize the same predictive algorithm.

4. RESULTS AND DISCUSSION

4.1. Analysis of the Proposed Approach

This conceptual research provides a comprehensive resource planning methodology based upon integrating predictive analysis with energy-aware infrastructure management. An important finding of the analysis is that the operational value of forecasting relates directly to the resource-related decisions being supported by such forecasts. Forecasting may provide opportunities to prepare capacity earlier than anticipated; however, operational efficiency (energy savings) and/or improved performance cannot be assumed to exist solely as a result of accurate forecasting. In addition, the framework emphasizes the need to consider more than one planning horizon. For example, short-term forecasting can assist with decision making regarding container scaling and placement of workloads, whereas longer-term forecasting can aid in decision making related to capacity reservations and infrastructure planning. It should be noted that a single planning horizon will likely not be appropriate for all decisions due to varying execution times and associated risks with each action taken, i.e., deploying a new server, moving a virtual machine, or adding additional container replicas. An additional significant feature of this type of system is that it separates the process of planning from that of executing. The forecasting service can provide recommendations, however there must be a separate policy layer that will assess if the recommendation is both appropriate and allowed. Separating these two functions is especially beneficial for enterprise systems where a technically possible action may be prohibited due to compliance regulations, scheduled maintenance activities, ownership of applications, or meeting availability targets. Feedback is also essential. When the actual demand does not match the forecast, the system must differentiate among normal forecasting errors, sudden changes in workload, telemetry failures, and delays in execution. Each of these situations will necessitate a unique response. For instance, a forecasting error might warrant a review of the model, whereas a delay in execution may necessitate adjusting the scaling lead time or the platform's configuration.

4.2. Performance Evaluation and Comparative Analysis

The performance assessment of the suggested predictive resource planning framework is based upon the energy usage, resource usage, workload prediction accuracy, response times, and operating expenses. To find out what the possible benefits are of the suggested framework compared to traditional methods for static resource allocation and reactive auto scaling in cloud computing and enterprise workloads, it is recommended that the two be evaluated together. Since there has been no data collected from an experiment, the tables and graphs that follow show examples of how the framework would perform if the data were collected in an actual experiment.

Table 1: Comparative Performance Evaluation of Resource Management Approaches

Performance Metric	Static Resource Allocation	Reactive Auto scaling	Proposed Predictive Framework
Average Resource Utilization (%)	45	65	80
Relative Energy Consumption (%)	100	85	70
Workload Prediction Accuracy (%)	Not Available	Not Available	90
Average Response Time (ms)	250	180	140
Relative Operational Cost (%)	100	85	72

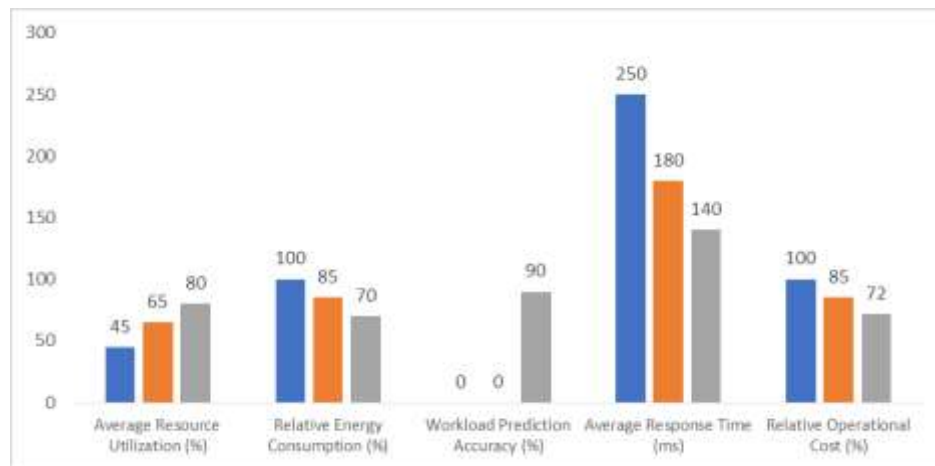


Fig 3 - Comparative Performance of Cloud Resource Management Approaches

4.3. Discussion, Implications, and Limitations

The suggested framework is applicable to the field of cloud platform engineering, the operation of an enterprise's infrastructure, and the area of sustainable computing research. The framework connects workload forecasting to the decision-making process concerning capacity and therefore offers a foundation on which to replace individual monitoring and scaling methods with a more integrated approach to managing resources. Additionally, the framework's focus on energy-awareness encourages infrastructure teams to assess how placement and consolidation decisions affect the environment as opposed to assuming that increasing the amount of used capacity results in superior performance. As far as the operations of an enterprise are concerned, the framework enables teams to manage workloads differentially. Critical business applications may maintain relatively high levels of excess capacity, while less critical batch workloads may be scheduled based upon projected demand and available capacity within the infrastructure. This methodology recognizes that various types of workloads possess different degrees of tolerance for latency, disruptions, and contention over resources. Furthermore, the methodology provides a conceptual framework for integrating technical resource decisions into business schedules and operational goals. The framework can also

enhance the quality of planning for capacity. Rather than being dependent solely on average historical data or subjective assessments of requirements, infrastructure teams can look at forecasted demand, predicted levels of uncertainty in that demand, resource limits, and actual results from past experiences. This type of information can assist with making decisions regarding reservations, expanding infrastructure, migrating workloads, and having discussions related to performance goals for applications. However, this approach does have some restrictions. One restriction is the lack of empirical validation. Although many of the elements of the framework are based upon well-known concepts for managing resources and forecasting, there has yet to be evidence presented that demonstrates how effective these elements are when implemented as a system. Another restriction is the variability of workload. Forecasting models that were developed using historical observation data may not produce accurate forecasts when there are major changes made to the architecture of an application, changes occur in the demand of a business, or unforeseen events take place. One additional restriction is the difficulty in measuring energy usage. Energy usage will vary depending upon the generation of hardware being used, the environment in which it operates, and the configuration of the infrastructure. Measurements taken at the level of servers will not always reflect the total energy consumed by a data centre since cooling and power distribution overhead will typically not be included in such measurements. To adequately assess the amount of energy used, transparent measurement boundaries must be established, and standardized reporting procedures must be utilized. Operational complexity is finally introduced within the framework. Forecasting services, telemetry pipelines, policy engines, and orchestration controls will all require reliable operation and security. If the recommendations provided are incorrect, it could lead to excessive scaling, unsafe consolidation, or frequent modifications to the infrastructure. Therefore, when deploying to production, there needs to be guardrails, audit logs, rollback mechanisms, access controls, and human oversight for decision making with significant impact. Overall, the above points demonstrate that predictive resource planning represents a viable path forward as a design approach to address the shortcomings of traditional auto scaling systems, but not necessarily a superior alternative in every scenario. To determine its practical utility, experimentations must be conducted using specific workloads while evaluating performance, energy consumption, costs, and reliability.

5. CONCLUSION

Predictive resource planning was investigated as a method to improve both the efficiency of energy use and the management of enterprise workloads in cloud computing environments. The study documented the shortcomings of static provisioning, reactive auto-scaling, and resource allocation based solely on current utilization. The authors developed a conceptual model that integrates workload telemetry, demand forecasting, energy-aware capacity planning, policy-controlled orchestration and continuous performance monitoring. The main contribution of the work is the development of a predictive intelligence based resource management decision making process subject to specific service, cost, and reliability requirements. Additionally, the author's stress that forecasts must enable actionable responses and that the outcomes of the actions must be evaluated rather than assumed. Lastly, the authors propose an evaluation strategy that will assess the predictive ability of the models developed, energy consumption, resource utilization, service performance,

operational costs and resilience. This is a research-based, conceptual paper which does not provide empirical evidence of reduced energy use or improved application performance; however, it does establish a formal structure that can be used to conduct experimental studies and/or test bed experiments. Additionally, this research provides value to both cloud engineers and business unit infrastructure personnel by providing them with an understanding of how to incorporate predictive planning into their larger, quantifiable sustainable computing plans. In addition to the aforementioned considerations, the ultimate effectiveness of the proposed methodology will depend upon the characteristics of the workload(s) being analysed, the accuracy of the predictions made, the capabilities of the infrastructure, and the overall quality of operational governance.

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