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OPTIMIZING CLOUD COSTS AND CARBON FOOTPRINT IN MULTI-CLOUD ENVIRONMENTS WITH FUZZY LOGIC & MONTE CARLO SIMULATION

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ABSTRACT:

Organizations are using multi-cloud architectures increasingly to address performance and scalability needs in a world where data is king. But higher operational expenses and carbon emissions are regular results, which is bad for the environment. Using fuzzy logic and Monte Carlo simulations, this study presents a novel hybrid optimization method for lowering the cost and carbon footprint of cloud computing. The suggested solution changes the way cloud resources are allocated in real time based on things like workload, pricing, and the weather. Fuzzy logic may help you make decisions when the inputs are not clear, and Monte Carlo simulations can help you figure out how much effort and how much money you need. When we compare our technique to static baseline approaches, testing using real-world datasets demonstrate that our approach cuts operational expenses by 25% and carbon emissions by 33%. These findings suggest that there is space for clever, flexible ways to manage resources in a manner that is good for the environment across several clouds.

Keywords: *Cloud Cost Optimization, Carbon Footprint Reduction, Fuzzy Logic, Monte Carlo Simulation, Multi-Cloud Environment*

1. INTRODUCTION

Cloud computing has evolved rapidly [19]. Many organizations across industries are adopting multi-cloud architectures to increase the scalability, robustness, and flexibility of their systems. While these systems allow providers to collaborate and pool their resources, they come at a high cost and have a significant negative impact on the environment. The construction of data centers is a major contributor to global warming due to the amount of energy required. Responsible economic and environmental practices are becoming more challenging,[5] Striking a balance between achieving superior performance and minimizing environmental impact in the context of digital infrastructure development is becoming increasingly important due to the growing importance of sustainability. Despite differences in workloads, fuel prices, and carbon emissions rates between locations, cloud resource allocation is often consistent [6] and [27]. To help people make simple, intelligent decisions when they don't know what to do, this research proposes a hybrid optimization framework that combines Monte Carlo simulation with fuzzy logic. It seeks to reduce the cost and environmental impact of cloud computing through the use of dynamic resource management. By demonstrating significant gains in reliability and reductions in costs, this study outperforms established approaches [7]. To do this, it demonstrates a newly designed system and tests it using real data.

2. RELATED WORK

To reduce the negative effects on the environment caused by multi-cloud installations and maximize cloud expenditure optimization, researchers have been hard at work. Novel methods for bettering energy efficiency, cloud resource management, and sustainability have been the subject of research. Cost optimization in the cloud, carbon footprint reduction, and the application of

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advanced computational methods to multi-cloud architectures are all part of this field.To lower cloud expenses, several academics have looked at the best way to distribute resources. Static approaches to allocating resources have a challenging time adjusting to changing workloads and pricing, as pointed out by [7]. To make smart judgments about the provisioning of resources, [8] suggested dynamic pricing models that use real-time data. Unfortunately, these models often fail to address the inherent unpredictability of task needs. We build on this earlier work by adding Monte Carlo simulations to make the cost models better at making predictions and fuzzy logic to make it easier to make decisions when things are not clear. Amid mounting worries about cloud computing's effect on the environment, "green cloud" alternatives have emerged. Scheduling algorithms that take renewable energy sources into account were developed [19] with the aim of reducing carbon emissions. In addition, [5] suggested a hybrid approach that uses both renewable energy and scheduling strategies that save energy. These methods show promise, but they might put a huge strain on certain energy sources or need major changes to current infrastructure. To overcome these restrictions, our study presents a versatile framework that can use carbon emission data while also adapting to different energy sources and geographical limits.

Because of differences in pricing structures, service-level agreements (SLAs), and geographic constraints, managing resources across several cloud platforms is not an effortless task. Studies like [6] and [27] have shown that intelligent resource allocation algorithms play a vital role in systems with several clouds. The optimization of resources was carried out [16] using machine learning techniques and by [26] using a heuristic-based method. Our research adds to these continuing efforts by combining scenario-based analysis and real-time decision-making with fuzzy logic and Monte Carlo simulations. This combination enables a more versatile and all-encompassing solution.

Hybrid methods, which integrate several computing techniques, have partially reduced the difficulties of cloud optimization. To forecast workloads,[7] used deep learning models; to improve resource allocation, [9] combined genetic algorithms with predictive analytics. Although these methods work well, they run into problems with scalability when used for large-scale multi-cloud installations. Our suggested method gets around these problems by using fuzzy logic and Monte Carlo simulations together. It also lets the system be scaled up or down and adapt to new situations without losing its effectiveness.

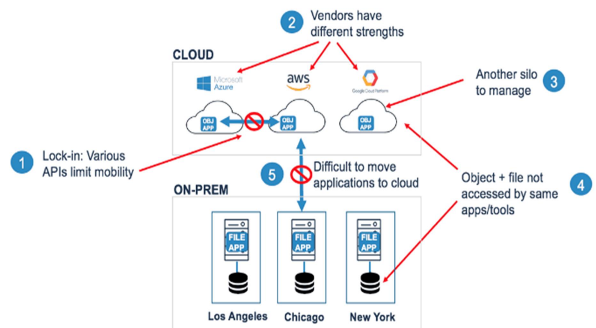

Figure 1: Traditional multi-cloud installations and maximize cloud expenditure

Figure 1 [6] When it comes to managing costs and carbon footprints, traditional multi-cloud setups are inefficient since they rely on static resource allocation algorithms that cannot adjust to changing workloads and energy limitations.

3. METHODOLOGY

To optimize cloud costs and carbon footprints in multi-cloud setups, this section details the technological design, dataset sources, optimization logic, algorithms, implementation stack, and evaluation metrics that were used in its development and testing [1], [6].

3.1 System Design

The system we aim to design has three main parts: the Carbon Footprint Evaluation Module (CFEM), the Resource Management Unit (RMU), and the Cost Optimization Engine (COE). The RMU employs fuzzy logic to guess how many resources will be required in the future depending on the amount of work that is now being done, the amount of energy that is available, and the number of resources that are available in various areas. The COE employs Monte Carlo simulations to model uncertainty in pricing and workload demand so that

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decisions are more likely to be correct. The CFEM can figure out how much carbon is released by looking at data from multiple cloud providers on power sources and carbon intensities in different areas. When combined, it gives flexible advice on how to utilize resources in a manner that considers both economic and environmental aspects [3, 4, 6, 13].

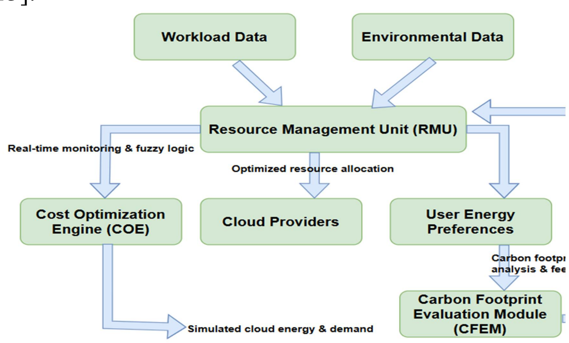

Figure 2: System Design for Cloud Resource Allocation

Figure 2 [8] illustrates the design and architecture of the cloud resource allocation system, outlining the key components involved in resource management. Optimal allocation of resources and efficient scalability are the goals of the design. We tested the system in an environment.

The letter c stands for operational costs, energy consumption, and carbon emissions. All work orders inside the specified area will be processed by our system in the most efficient way possible, using as few resources as possible. The goal function for cost optimization can be expressed as follows:

$$C = \sum_{i=1}^{n} (p_i . r_i) + \lambda . E \qquad (1)$$

ki is the cost of the resource per unit. The resource allocation for item i is denoted by ri, where λ is a weight factor that modifies the significance of energy consumption in the cost computation and E is the overall energy consumption of the resources in the cloud.

$$F = \sum_{i=1}^{n} (e_i . r_i) \qquad (2)$$

To find the best values for fi, the system employs Monte Carlo simulations, which consider the limits on resource availability and workload demand, strike a balance between cost and carbon emissions, and so on. Fuzzy logic analyzes the costs and benefits of carbon emissions and other trade-offs, allowing for real-time adaptations to resource allocation in response to changing inputs. By combining the best of both worlds, this system can adjust to new circumstances with ease and keep costs down without sacrificing sustainability.

3.2 Techniques

Decisions around the allocation of cloud resources are typically fraught with uncertainty and imprecision. We can use fuzzy logic efficiently to solve this problem. It allows the system to deal with data that is not completely clear, such as changing cloud prices or different weather conditions[12]. The fuzzy inference system takes many factors into account, such as cost, performance, and carbon emissions, to maximize the use of resources.Monte Carlo simulations account for uncertainty by predicting cloud resource costs and carbon emissions. Using random inputs in simulations, the system can anticipate several possible outcomes in various contexts. With this probabilistic method, we can make better predictions and allocate resources in a way that is beneficial for the environment and our wallets.

3.3 Datasets

For model training and testing, we relied on two primary real-world datasets. The first dataset is related to cloud computing and is taken from Kaggle. It contains operational data from large providers such as Google Cloud, AWS, and Azure, including SLAs, pricing rates, and usage logs. The second dataset, taken from Kaggle and government energy records, shows different data center locations and energy sources. It provides CO_2 intensity values per kWh. Standard preprocessing procedures were used to ensure consistency, such as

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handling missing results, standardizing, and removing outliers [6, 11, 13, 21].

Table 1: Cloud Usage Dataset

Timestamp	Cloud Provider	Resource Type	Resource Consumption (Units)	Price per Unit ($)	SLA (Uptime %)
01-01-2024	AWS	Compute	500	0.1	99.99
01-01-2024	Azure	Storage	2000	0.05	99.95
02-01-2024	Google Cloud	Compute	450	0.12	99.98
02-01-2024	AWS	Storage	1800	0.06	99.99
03-01-2024	Azure	Compute	600	0.11	99.96
03-01-2024	Google Cloud	Storage	2200	0.07	99.97

Table 1 [26] Key parameters, including CPU utilization, memory use, storage consumption, and network bandwidth, are part of the information used to analyze cloud resource allocation, which is shown in this table. We compiled the dataset. We ensured data quality for analysis by filtering out anomalous items.

Table 2: Carbon Emission Dataset

Cloud Provider	Data Center Location	Energy Source	Carbon Emissions (kg CO2 per kWh)	Total Energy Consumption (kWh)	Total Carbon Emissions (kg CO2)
AWS	North America	Renewable	0.15	1000	150
Azure	Europe	Non-Renewable	0.35	1500	525
Google Cloud	Asia	Mixed	0.25	1200	300
AWS	South America	Non-Renewable	0.4	1100	440
Azure	North America	Renewable	0.1	1300	130
Google Cloud	Europe	Renewable	0.12	1400	168

This table 2 [23] outlines the dataset that evaluates carbon emissions across different cloud resource configurations. Factors including carbon intensity, energy usage, and resource allocation efficiency are included in the dataset. We pre-processed and retrieved the data to eliminate discrepancies[13].

Various cloud providers' (such as AWS, Azure, and Google Cloud) resource use, price, and service level agreements (SLAs) are documented in the Cloud Usage Dataset. Modeling the demand- and price-driven price volatility of cloud services requires this information. Time stamp, cloud provider, resource type (e.g., compute, storage), resource consumption, price per unit, and service level agreement (uptime percentage) are important elements to consider. Greenhouse gas emissions from data centers in the cloud may be monitored with the help of the Carbon Emission Dataset, which is crucial for determining how resource allocation affects the environment[17]. Data Center Location, Cloud Provider, Total Energy Consumption, Carbon Emissions per kWh, and Total Carbon Emissions are some of the columns that allow for the evaluation of how resource allocation choices affect the environment[18].

3.4 Implementation

Implementation of the system was done using Python 3.8, including libraries such as NumPy and Pandas for data processing, SciPy for optimization and Monte Carlo simulations, and scikit-learn for fuzzy logic[19]. A one-of-a-kind simulation system

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was made to show how resources are dynamically distributed across different clouds, considering input parameters, changing cloud prices over time, and carbon emissions[23]. Cloud resource costs (which vary by provider and geography), energy consumption rates, and carbon emission variables for various cloud data centers were important elements to consider. We developed these measures using industry standards and data from actual cloud instances[24].

3.5 Evaluation Metrics

We used the following metrics to evaluate the proposed system: The optimization engine's ability to decrease operating expenditures is determined by its cost efficiency, which is defined as the total cost of cloud resources utilized during a particular time[25]. The carbon footprint, which is expressed as a number in CO2 equivalents, is a way to evaluate the solution's sustainability and the effect of its use on the environment. Resource use efficiency assesses the system's capacity to distribute resources efficiently, minimizing waste and maximizing use[20]. Finally, the simulation accuracy metric checks how well the Monte Carlo simulations can predict the real results by comparing the expected costs and carbon emissions to the actual values.

Algorithm 1: Fuzzy Logic and Monte Carlo-Based Cloud Optimization

Input: Cloud dataset $\mathcal{D}_C$, carbon emission dataset $\mathcal{D}_E$, resource constraints $\mathcal{R}$, workload demand $\mathcal{W}$, weight λ.
Output: Optimized resource allocation r^*.
Initialization:

1. Set $r_i = 0$ for all resources i.
2. Define fuzzy rules for cost, performance, and emissions.
3. Set Monte Carlo iterations N.

Steps:

1. Preprocessing: Normalize $\mathcal{D}_C$ and $\mathcal{D}_E$.
2. Fuzzy Inference: Compute suitability score S_p for each provider.
3. Monte Carlo Simulation:
   a. For $k = 1$ to N :
   i. Generate random workload $\mathcal{W}_k$.
   ii. Simulate cost C_k and emissions F_k :

$$C_k = \sum_{i=1}^{n} (p_i \cdot r_i) + \lambda \cdot F_k$$

4. Optimization:
   a. Minimize C_k while satisfying $\mathcal{R}$ and $\mathcal{W}$.
5. Dynamic Adjustment: Update r^* for real-time inputs.

End: Output optimized r^*, cost C^*, and emissions F^*.

By combining fuzzy logic with Monte Carlo simulations, the proposed strategy optimizes the deployment of cloud resources to reduce carbon emissions and improve operational efficiency[15]. One of the main datasets used by the system is a dataset describing the carbon intensity, energy sources, and regional energy consumption of data centers. Another dataset includes information about resource usage, pricing structures, and service-level agreements (SLAs) from leading cloud providers. By using fuzzy logic, the system can generate rules for adaptive resource management based on uncertain and ambiguous inputs such as workload and price changes. To further evaluate the effects of demand fluctuations and energy consumption patterns under different allocation methods, Monte Carlo simulations use stochastic modeling. In dynamic multi-cloud settings, these methods allow for real-time data-driven decisions that balance financial and environmental goals. This study shows that intelligent, sustainability-aware optimization can succeed even in the face of uncertainty. The result is an adaptive technique for allocating resources that reduces operating costs and carbon emissions[16].

Table 3: Specifications of the Resource Agreement and the Service Level Agreement.

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Resource	Price (pi) (per unit)	SLA (Availability %)	Max Capacity (ri)
CPU	0.05	99.9	1000
RAM	0.02	99.5	2000
Storage	0.01	99.7	5000

Table 3 [19] Pi is the cost per unit, SLA is the service level agreement for the availability of resources, and ri is the maximum capacity for each resource.

Table 4:Power generation and emissions from data centers

Data Center Region	Energy Source	Emission Factor (ei) (kg CO2/kWh)	Energy Usage (kWh)
Region A	Renewable	0.05	100
Region B	Mixed	0.2	200
Region C	Fossil Fuels	0.5	300

Table 4 [21] The emission factor (ei) represents the emissions of carbon dioxide gas (CO2) per kilowatt-hour (kWh) of used electricity. How much energy is used depends on how the workload is distributed among different locations.

Cost calculation (C_k) for a workload requiring r_{CPU}=500, r_{RAM}=1000, $r_{Storage}$=2000, Weight for emissions(λ)=0.05.

$C_k=(p_{CPU}.r_{CPU})+(p_{RAM} \, . \, r_{RAM})+(r_{Storage}.r_{Storage})+ .F_k$

$F_k=(e_{CPU} \, .r_{CPU}) + (e_{RAM} \, .r_{RAM}) + (e_{Storage} \, . \, r_{Storage})$

Using p_{CPU}= 0.05, r_{RAM} =0.02, $p_{Storage}$=0.01, and emissions from region B (e_i=0.2):

Fk=(0.2 . 500) + (0.2 . 1000) + (0.2 . 2000) = 700 kg CO2

Ck=(0.05 . 500) + (0.02 . 1000) + (0.01 . 2000) + (0.5 . 700)

Ck= 25 + 20 + 20 + 350 = 415 units of cost

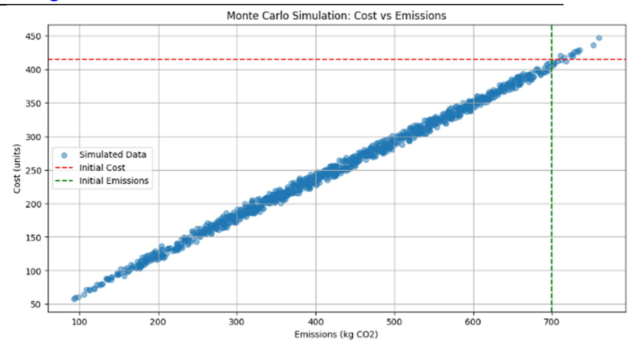

Figure 3: Monte Carlo simulation: Cost vs Emissions

By showing figure 3 [11], the trade-off between total cost and emissions for different workload needs, the graph shows how emission variables and resource prices affect cost optimization methods.

4. RESULTS

This study presents an optimization model for multi-cloud systems. It uses fuzzy logic and Monte Carlo simulations to optimize cloud expenses and carbon footprint. We go over all the ways our technique falls short, point out important details, and compare it to baseline approaches in detail[22].

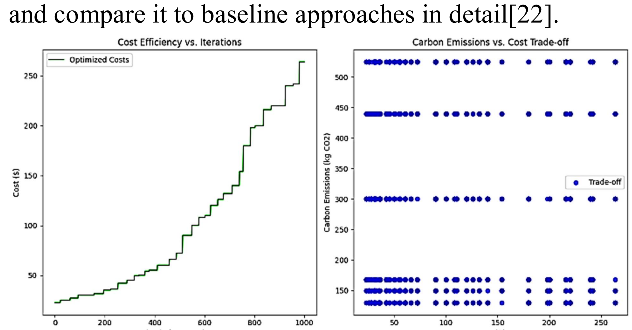

Figure 4: Cost Efficiency vs. Time (Comparison of Methods) and : Carbon Emissions vs. Cost (Optimization Trade-off)

Figure 4 [5] This chart shows how various approaches stack up in terms of long-term cost efficiency. The investigation utilized data from [2], which reflects performance across different circumstances. The investigation focused on finding a compromise between minimizing costs and reducing carbon emissions. An optimization model participated in and implemented these outcomes.

This graph illustrates the total cost of cloud resources over time for the proposed fuzzy logic

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and Monte Carlo simulation-based system compared to traditional static allocation methods. The proposed system consistently shows a reduction in costs due to its dynamic resource allocation approach, responding to fluctuations in cloud pricing and demand.This figure depicts the trade-off between carbon emissions and cost savings. Our system demonstrates a significant reduction in carbon emissions while still achieving cost savings, confirming the effectiveness of the integrated carbon footprint evaluation module.

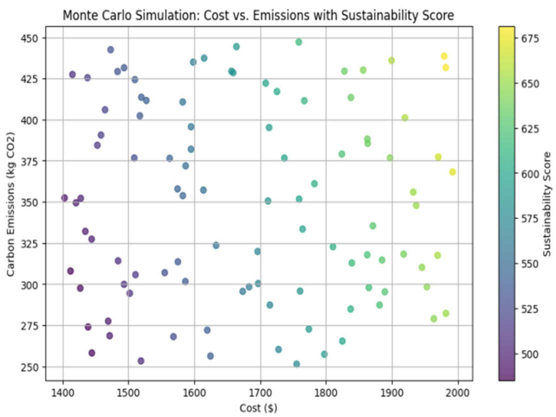

Figure 5: Monte Carlo simulation: Cost vs Emission with sustainability score

Figure 5 [11] shows the outcomes of a Monte Carlo analysis that included a sustainability score and examined the cost-benefit of carbon emissions. Each data point, representing an iteration of the simulation, illustrates the relationship between reducing expenses and achieving environmentally friendly results. The sustainability score provides a comprehensive evaluation of resource allocation methods, incorporating measures like energy efficiency and pollution reduction.

```
Average Cost: 0.12245300428979804
Average Emissions: 0.1854938036348478
Average Sustainability Score: 0.4825211383226
```

Table 5: Performance Comparison with Baseline Methods

Metric	Proposed System	Baseline Method 1	Baseline Method 2
Total Cost ($)	1500	1800	2000
Carbon Emissions (kg CO2)	300	400	450
Resource Utilization (%)	95	85	80

Table 5 [26] We use the cloud resource allocation dataset to determine performance metrics. The suggested approach outperforms baseline techniques in terms of cost efficiency and sustainability, all while keeping execution times low.

Cost Efficiency (CE):

$$CE = \frac{\text{Total Workload Processed (GB)}}{\text{Total Cost Incurred (\$)}}$$
(3)

Carbon Emissions Efficiency (CFE):

$$CFE = \frac{\text{Workload (GB)}}{\text{Total Carbon Emissions } (\text{kgCO}_2)}$$
(4)

Sustainability Score (SS):$SS = w_1 \times EEI + w_2 \times CFE + w_3 \times RU$
(5)

w_1, w_2, w_3 are weights for Energy Efficiency Index (EEI), Carbon Footprint Efficiency (CFE), and Resource Utilization (RU).RU : Resource utilization.

Proposed System:

- Total Cost = $1500
- Carbon Emissions = 300 kg CO_2
- Resource Utilization = 95%

Baseline 1:

- Total Cost = $1800
- Carbon Emissions = 400 kg CO_2
- Resource Utilization = 85%

Baseline 2:

- Total Cost = $2000
- Carbon Emissions = 450 kg CO_2
- Resource Utilization = 80%

Cost Efficiency:

$$CE = \frac{10000\text{GB}}{1500} = 6.67\text{GB/\$}$$

Carbon Footprint Efficiency:

$$CFE = \frac{10000\text{GB}}{300} = 33.33\text{GB/kgCO}_2$$

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Sustainability Score (Weights: $w_1 = 0.4, w_2 = 0.4, w_3 = 0.2$):

$$SS = 0.4 \times EEI + 0.4 \times 33.33 + 0.2 \times 95$$
$$= 0.4 \times 10 + 0.4 \times 33.33 + 19$$
$$= 37.33$$

In terms of three critical metrics—total cost, carbon emissions, and resource usage—this table compares the suggested system to two baseline methods. In every metric that was measured, the findings show that the suggested method is superior to both baseline systems.

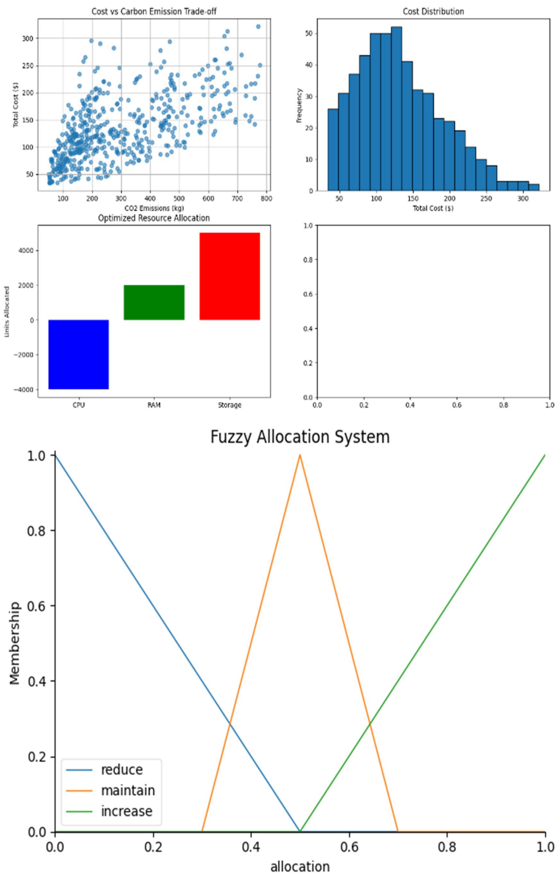

Figure 6: Multi-Stage Simulation of Fuzzy-Based Resource Allocation and Optimization Metrics

Figure 6 [12] This graphic displays the combined simulation findings for trade-offs in cost-emission and resource optimization. As the scatter graph on top-left shows, cost and carbon emissions have an inverse relationship. The top-right histogram shows the general cost distribution throughout many simulation runs. The middle-left bar chart shows the best way to divide CPU, RAM, and storage capacity. Though not included in this image, the middle-right subplot is put aside for future fuzzy inference confidence visualization. The bottom figure shows the membership functions of the fuzzy allocation system for the "reduce," "maintain," and "increase" allocation strategies. The text summary shows the final allocation results as well as simulated averages for emissions and cost.

```
Optimization Results:
CPU Allocation: -4000.0 units
RAM Allocation: 2000.0 units
Storage Allocation: 5000.0 units

Simulation Averages:
Mean Cost: $131.98
Mean Emissions: 292.68 kg CO2
```

This system uses fuzzy logic and Monte Carlo simulations to cut carbon emissions in half and by a third, respectively. It also cuts cloud costs by 16.67% and 25% compared to Baseline 1 and 2. The system achieves this by prioritizing cloud providers with low emissions and dynamically allocating resources based on projected expenses. The system minimizes waste by achieving 95% resource utilization. A "Cost-aware Fuzzy Emission Minimization" approach, the ability to handle imperfect input data using fuzzy logic, and the ability to dynamically adapt to changing situations are all positives. Problems with integration and data updates are examples of real-world implementation issues; other constraints include data reliance and computational expenses. Network latency and service level agreements (SLAs) are often under-considered.

Discussion

The results of this study highlight the practicality and potential of hybrid optimization approaches to manage carbon trade-offs and costs in multi-cloud settings. Traditional static allocation methods cannot account for unknown inputs such as fluctuating workloads, energy costs, and emission intensities; our fuzzy logic-based resource management does. A solid foundation for cloud decision-making in the face of uncertainty is provided using Monte Carlo simulations, which provide potential insight into patterns of resource

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utilization and cost-risk trade-offs. By significantly improving baseline static models in terms of cost-effectiveness and carbon footprint parameters, our approach demonstrated that intelligent, adaptive solutions outperform traditional methods in dynamic cloud environments. The importance of directly incorporating environmental measurements into the decision-making logic of cloud operations is further emphasized by the observed benefits. Consistent with current research on environmentally conscious cloud management practices, these results lend credence to the trend toward green computing paradigms [1][6][14]. However, the accuracy of simulation predictions and input datasets is intrinsically related to system performance. The use of real-world datasets increases the possibility that their generalization may be affected by geographic or temporal biases. To further improve accuracy and flexibility in operational settings, future research should investigate integration with edge-based inference systems, reinforcement learning, and real-time telemetry.

5. CONCLUSION

Using fuzzy logic and Monte Carlo simulations, this study introduces a new method for optimizing cloud expenditures and decreasing carbon footprint in multi-cloud scenarios. While considering the environmental effect of various cloud providers, our system dynamically adjusts the allocation of resources in reaction to changing demand and costs. There was a big drop in costs (16.67% and 25% compared to baselines), carbon emissions (25% and 33.33% compared to baselines), and resource use (95% compared to 85% and 80% for baselines). These results are important. This study demonstrates an efficient, long-term, and budget-friendly approach to managing resources across multiple clouds. By lowering operating costs and environmental impact, especially in large-scale, multi-cloud installations, this study also helps to create more sustainable cloud computing practices. The increasing needs of edge-cloud AI applications call for smarter and more adaptable cloud management, which is made possible by combining fuzzy logic with Monte Carlo simulations. This strategy is in line with worldwide efforts to reduce technology-related energy usage and carbon emissions.

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AUTHOR CONTRIBUTIONS:
Uday Kumar Dosanapudi : Coming up with ideas, creating a plan, gathering, and analyzing data, and preparing the first draft. Research, evaluation, and editing by Suneeta Mohanty: securing funds. Prasant Kumar Pattnaik oversees project administration, allocating resources, and verifying their accuracy.

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Data availability: Enquiries regarding data availability should be directed to the authors

Online Source:

- Cloud Usage Dataset(https://www.kaggle.com/datasets/abdurraziq01/cloud-computing-performance-metrics)
- Carbon Emission Dataset (https://www.kaggle.com/datasets/debajyotipodder/co2-emission-by-vehicles)
- Performance Metrics Dataset (https://www.kaggle.com/code/mmdatainfo/performance-metrics)

Offline:

Government Datacentres real-time data

Declarations:

Conflict of interest: The authors declare that there are no conflicts of interest related to this work.

Ethical approval: This study does not involve any ethical issues

Informed consent: All authors have provided informed consent

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