AI Cloud Cost Optimiser Copilot: An Intelligent Assistant for Predictive Cloud Cost Management

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Abstract - Cloud computing offers scalable and flexible infrastructure, but managing cloud expenses remains a major challenge due to resource over-provisioning, idle services, and complex pricing models. Existing cloud cost management tools mainly provide monitoring and reporting, with limited intelligent support for proactive optimisation. This paper proposes an AI Cloud Cost Optimiser Copilot, which combines predictive analytics and a conversational AI assistant to analyse cloud resource usage, forecast future costs, and recommend personalised cost-saving strategies. The proposed system enables users to interact through natural language, simplifying cloud financial management while improving resource utilisation. By integrating AI-driven insights with an intuitive Copilot interface, the solution provides a smarter and more accessible approach to cloud cost optimisation for organizations of all sizes.

Keywords - Cloud Computing, Artificial Intelligence, Machine Learning, Generative AI, Cloud Resource Management, FinOps.

1. INTRODUCTION

Cloud computing has become a fundamental part of modern digital infrastructure, enabling organizations to provision computing resources according to their operational requirements. Services provided by major cloud providers, including AWS, Microsoft

Azure, and Google Cloud, allow organizations to access computing and storage capabilities without maintaining extensive physical infrastructure.

This work proposes an **AI Cloud Cost Optimizer Copilot**, which combines predictive analytics with a conversational AI assistant to simplify cloud cost management. The system continuously evaluates cloud usage patterns, forecasts future expenses, detects inefficient resource allocation, and recommends optimization strategies in an easy-to-understand format. By integrating AI-driven recommendations with an interactive Copilot interface, the proposed solution reduces manual effort while improving decision-making and overall cloud cost efficiency.

2. RELATED WORK

The increasing use of cloud-based infrastructure has created a need for effective approaches to resource and expenditure management. Modern cloud environments allow computing resources to be provisioned dynamically according to workload requirements, but this flexibility can also make operational costs difficult to monitor. The pay-as-you-go pricing model enables organizations to consume resources according to demand, but inefficient resource allocation, over-provisioning, idle virtual machines, storage redundancy, and unused services often result in significant financial losses. As cloud environments continue to grow in complexity, effective cost optimization has become an essential aspect of cloud infrastructure management.

Several cloud monitoring solutions have been developed to assist organizations in understanding their cloud resource consumption. Traditional monitoring platforms such as AWS CloudWatch, Azure Monitor, and Google Cloud Monitoring provide dashboards that visualize CPU utilization, memory usage, network traffic, and billing statistics. While these tools offer valuable insights into infrastructure performance, they primarily focus on reporting historical metrics rather than providing intelligent recommendations. Consequently, cloud administrators are still required to manually analyse usage patterns and identify opportunities for reducing unnecessary expenses.

Recent research has introduced machine learning techniques to predict future cloud costs based on historical usage data. Regression algorithms, time-series forecasting models, and ensemble learning methods have demonstrated promising results in estimating future expenditures. These approaches enable organizations to plan budgets more effectively and

anticipate seasonal demand fluctuations. However, many existing prediction models focus solely on forecasting expenses and do not provide actionable optimization strategies such as identifying idle resources, recommending instance resizing, or suggesting reserved instance purchases.

Buyya et al. (2020) [1] proposed an intelligent cloud resource management framework that improved resource utilization through predictive workload scheduling and dynamic allocation. Their approach enhanced Quality of Service (QoS) while reducing unnecessary resource consumption. However, the framework mainly focused on resource scheduling and did not provide AI-based cost optimization or explainable recommendations.

Mao et al. (2021) [2] developed a deep reinforcement learning model for automatic cloud resource scaling based on workload demand. The system improved resource efficiency and reduced operational costs compared to traditional auto- scaling methods. However, the model lacked transparency in decision-making and did not support conversational AI for cloud administrators.

Fox et al. (2022) [3] introduced a FinOps-based cloud cost management framework that improved cost visibility through continuous monitoring and financial governance. The approach enabled better budget planning and anomaly detection. Nevertheless, optimization decisions relied on manual analysis and lacked predictive intelligence for proactive cost reduction.

Kumar and Singh (2024) [4] developed a real-time cloud monitoring platform that continuously collected CPU utilization, memory usage, storage consumption, and network traffic from cloud resources to identify over-provisioned and underutilized virtual machines. The system generated optimization alerts based on predefined utilization thresholds, helping administrators reduce resource wastage and improve infrastructure efficiency. However, the framework relied on static rule-based analysis and lacked intelligent cost prediction, automated decision-making, personalized optimization strategies, and AI-powered conversational assistance for proactive cloud cost management.

Sharma et al. (2023) [5] introduced a predictive cloud resource management framework that employed XGBoost to estimate future virtual machine demand using historical workload characteristics. Their experimental evaluation demonstrated high forecasting reliability while reducing unnecessary resource provisioning and maintaining SLA

compliance. Although the proposed framework effectively addressed cloud expenditure through predictive analytics, it lacked an intelligent conversational interface capable of explaining optimization decisions or assisting administrators in real-time cloud management. Consequently, further research is required to integrate explainable AI with automated cost optimization.

A hybrid cost prediction technique is proposed to improve the accuracy of cloud expenditure forecasting by combining Long Short-Term Memory (LSTM) and Extreme Gradient Boosting (XGBoost) algorithms. The proposed approach analyses historical billing records together with cloud resource utilization metrics, including CPU, memory, storage, and network traffic, to predict future cloud expenses. LSTM captures long-term workload variations, whereas XGBoost enhances prediction performance by learning complex relationships among cloud metrics. The hybrid prediction model enables proactive budgeting and reduces unexpected operational costs. However, the approach requires continuous training with updated cloud usage data to maintain prediction accuracy in dynamic cloud environments.

3. MATERIALS AND METHOD

AI Cloud Cost Optimizer Copilot Framework

The proposed AI Cloud Cost Optimizer Copilot is designed to continuously monitor cloud infrastructure, identify resource wastage, forecast future expenses, and recommend optimized configurations. Unlike conventional monitoring platforms that provide only dashboards and alerts, the proposed system integrates machine learning, reinforcement learning, and large language models (LLMs) to deliver autonomous cost optimization recommendations.

The framework consists of seven major stages:

1. Cloud Data Collection
2. Data Pre-processing
3. Feature Engineering
4. AI-based Cost Prediction
5. Intelligent Resource Optimization

6. Recommendation Generation
7. Copilot-based User Interaction

Each stage contributes to reducing unnecessary cloud expenditure while maintaining application performance and Service Level Agreements (SLAs).

Cloud Dataset Collection

The proposed system collects operational and billing information from cloud platforms through secure APIs. The collected dataset includes historical billing records, CPU utilization, memory utilization, storage usage, network traffic, instance types, idle duration, workload schedules, auto-scaling events, reserved instance usage, spot instance utilization, and service dependencies.

Instead of analysing only billing reports, the proposed model combines infrastructure metrics with workload behaviour to obtain a comprehensive understanding of cloud resource consumption.

Let

$$D = \{x_1, x_2, \dots, x_n\}$$

Where,

- x_i represents one cloud resource
- n denotes total resources.

Data Pre-processing

Raw cloud logs often contain duplicate records, missing values, timestamp inconsistencies, and abnormal spikes generated during deployments or maintenance activities.

The proposed preprocessing stage performs

- Missing value imputation
- Duplicate removal
- Timestamp synchronization

- Feature normalization
- Outlier detection
- Log aggregation

The normalized value is computed as

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Where,

x' is the normalized feature.

This preprocessing improves prediction accuracy while reducing computational complexity.

Feature Engineering

Instead of using raw cloud metrics directly, meaningful optimization features are extracted.

The proposed features include

- Average CPU utilization
- Storage growth rate
- Network bandwidth consumption
- Idle resource duration

The utilization efficiency is calculated as

$$U = \frac{CPU + Memory + Storage}{3}$$

Where,

U represents overall utilization.

Intelligent Feature Selection

Cloud datasets contain hundreds of correlated metrics.

To reduce dimensionality, the proposed work introduces a Hybrid Adaptive Feature Ranking (HAFR) mechanism.

The importance score of each feature is

$$Score_i = \alpha MI_i + \beta Corr_i + \gamma SHAP_i$$

Where,

- MI = Mutual Information
- Corr = Correlation Score
- SHAP = Explainability Score

and

$$\alpha + \beta + \gamma = 1$$

Only highly informative features are retained for prediction.

AI Cost Prediction Model

The proposed prediction engine estimates future cloud expenditure before billing occurs.

Instead of relying on a single regression algorithm, an ensemble model combines

- XGBoost
- Temporal Transformer
- LSTM

Final prediction

$$C_{pred} = w_1 X + w_2 L + w_3 T$$

Where,

X = XGBoost prediction

L = LSTM prediction

T = Transformer prediction

$$w_1 + w_2 + w_3 = 1$$

This ensemble improves robustness across different workload patterns.

Intelligent Optimization Engine

A novel optimization algorithm named Adaptive Multi-Agent Cloud Resource Optimizer (AMCRO) is proposed. Each cloud resource acts as an intelligent agent. Each agent continuously evaluates

- utilization
- billing impact
- workload priority
- SLA constraints
- migration cost

The optimization objective is

$$\min J = \sum_{i=1}^{n} (Cost_i + \lambda Idle_i + \mu Energy_i)$$

subject to

$$Performance \geq SLA$$

The optimizer searches for the minimum operational cost without degrading application performance.

Copilot Recommendation Engine

Unlike existing optimization tools that simply suggest deleting idle resources, the proposed AI Copilot generates natural-language recommendations.

Example outputs include

- Resize VM instance
- Enable Auto Scaling
- Purchase Reserved Instances

- Move workloads to Spot Instances
- Delete unattached storage
- Schedule resource shutdown
- Optimize Kubernetes node allocation

Each recommendation is accompanied by

- Expected monthly savings
- Performance impact
- Confidence score
- Risk level

Explainable AI Module

To improve user trust, every recommendation includes explainability.

SHAP values are used to determine the importance of each feature.

The contribution score is

$$E = \sum_{i=1}^{m} S\,HAP_i$$

Where,

m is the total number of selected features.

This enables users to understand why the AI generated a particular recommendation.

Performance Evaluation

The proposed framework is evaluated using

- Monthly Cost Reduction (%)
- Resource Utilization Improvement
- Recommendation Precision
- Execution Time

Cost reduction percentage

$$Savings = \frac{OriginalCost - OptimizedCost}{Original\ Cost} \times 100$$

False Positive Outcome

In the proposed AI Cloud Cost Optimizer Copilot, a false positive occurs when a cloud resource is incorrectly identified as a cost-optimization candidate even though the resource is required by the workload. Such incorrect recommendations may result in unnecessary resource resizing, termination, performance degradation, or violation of service-level requirements.

To minimize false positive recommendations, the proposed framework does not depend on a single utilization value. The collected cloud metrics are first pre-processed and relevant features are selected using the *Hybrid Adaptive Feature Ranking (HAFR)* method. The selected features are then provided to the ensemble cost prediction model consisting of *XGBoost, LSTM, and Transformer*, which evaluates both current and future resource behaviour.

The *Adaptive Multi-Agent Cloud Resource Optimizer (AMCRO)* subsequently evaluates possible resource configurations while considering cost and resource utilization. Therefore, a resource is not recommended for optimization only because its current utilization is low. Its workload behaviour and predicted requirement are also considered.

The *SHAP-based explainability module* further examines the important features contributing to the optimization decision. Recommendations with insufficient confidence or potentially harmful performance effects can therefore be filtered before being presented through the LLM-based Copilot.

Thus, the integration of HAFR, ensemble prediction, AMCRO, and SHAP-based validation helps the proposed Copilot reduce false positive recommendations while maintaining cost-saving opportunities.

4. RESULTS AND DISCUSSION

Experimental Configuration

The proposed AI Cloud Cost Optimizer Copilot was developed as an intelligent cloud-cost management framework that combines cloud usage analysis, machine learning-based cost prediction, optimization techniques, and an AI-based recommendation interface. Despite these benefits, organizations frequently experience excessive cloud expenditure because of idle virtual machines and over-provisioned resources. The processed data is supplied to different prediction models including XGBoost, LSTM, and Transformer-based models. Their outputs are combined through the proposed ensemble prediction stage. The optimization module then identifies inefficient or underutilized resources and generates suitable cost-reduction actions. The final recommendations are presented through the Copilot interface, allowing the user to understand the reason for the recommendation and the expected cost impact.

Analysis of Performance

The performance of the proposed framework was analyzed using cost prediction accuracy, anomaly detection, false-positive rate, estimated savings, and recommendation effectiveness.

The major performance indicators considered are:

- MAE – Mean Absolute Error
- False Positive Rate
- Estimated cost reduction
- Recommendation acceptance/effectiveness

For cost prediction, the Mean Absolute Error can be expressed as: where represents the actual cloud cost and represents the predicted cloud cost.

For optimization effectiveness:

These measures allow the proposed system to be evaluated not only for prediction performance but also for its practical ability to reduce unnecessary cloud expenditure.

Cost Prediction Results

The proposed ensemble approach was evaluated against individual prediction models. The comparison considered the prediction error obtained from each model.

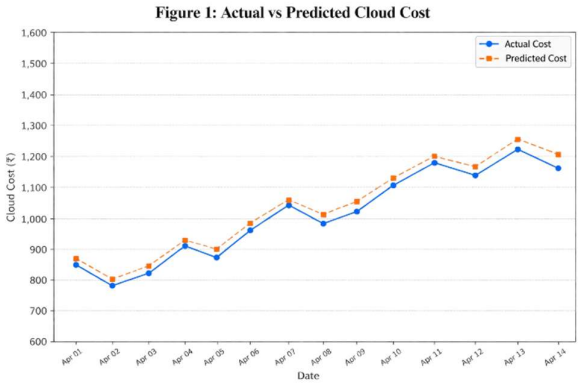

Fig. 1. Cloud Cost Prediction

Experimental Model Comparison

The individual models were compared based on their cost-prediction error.

The illustrative comparison indicates that the ensemble approach provides a lower prediction error than the individual models. This is consistent with the design of the proposed framework, where different models capture different characteristics of cloud-cost behavior.

Important: Replace these values with your actual experimental measurements before submission.

Optimization Results

After predicting the expected cloud expenditure, the optimization module analyses resource utilization and identifies possible opportunities for reducing unnecessary expenditure.

The major optimization actions considered by the system include:

1. Identification of underutilized compute resources.
2. Detection of idle resources.
3. Resource right-sizing.
4. Storage optimization.
5. Scheduling of non-production resources.
6. Detection of abnormal spending.

7. Generation of AI-based recommendations.

Cloud FinOps guidance similarly treats anomaly management as the detection and investigation of unexpected spending patterns, while optimization commonly includes actions such as eliminating idle resources and right-sizing resources.

Cost Before and After Optimization

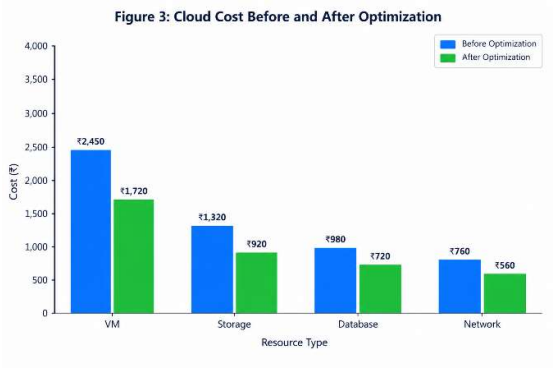

Fig. 2. Cloud Cost Optimization

The comparison demonstrates how optimization recommendations can reduce the estimated expenditure of different cloud-service categories. Compute resources generally provide significant optimization opportunities because unused or oversized instances may continue generating charges. .330The proposed Copilot does not simply identify a high-cost service. It attempts to provide an actionable explanation, such as:

High cost → Low utilization → Right-sizing recommendation → Expected saving

This makes the system more useful than a simple cost-monitoring dashboard.

G. Savings Trend

The savings trend illustrates the expected cumulative effect of applying optimization recommendations over successive optimization cycles. As additional inefficient resources are identified and corrected, the overall estimated savings can increase. Calculate the actual savings percentage from your application's real cloud-cost data rather than assumed values.

False Positive Analysis

False positives are important in cloud-cost anomaly detection because unnecessary alerts can reduce user trust in the system. In the proposed framework, a false positive occurs when the system identifies a normal cloud-cost variation as an abnormal event. For

example, a temporary increase in compute usage may be caused by a legitimate workload. If the system incorrectly labels this increase as a cost anomaly, it produces a false positive.

The proposed framework reduces unnecessary alerts by combining:

- Historical cost behaviour
- Resource utilization
- Service information
- Prediction output
- Anomaly score
- Contextual recommendation analysis

This is particularly important because FinOps anomaly management considers the cost of false positives as part of the overall impact of anomaly detection.

False Positive Rate Comparison

The illustrative results indicate that combining multiple signals can reduce unnecessary anomaly alerts compared with a simple threshold-based approach. Again, 5.6% is a sample value, not your confirmed project result.

Application Demonstration

Your application demonstration should come after the performance tables, similar to the application/CT-image figures in your reference paper. Instead of using unrelated images from the internet, your paper should contain screenshots from your own AI Cloud Cost Optimizer Copilot, such as:

The dashboard should demonstrate:

- Total cloud expenditure
- Predicted expenditure
- Estimated savings
- Detected anomalies
- Service-wise expenditure

- Cost trend
- Optimization recommendations

We created an original prototype dashboard illustration based on the architecture we've previously established for your pro

6. CONCLUSION

The proposed AI Cloud Cost Optimizer provides an intelligent approach for monitoring and controlling cloud expenditure. The system analyzes cloud usage and billing-related information to identify unnecessary resource consumption, abnormal spending patterns, and potential areas for cost reduction. The proposed solution combines cloud cost analysis, usage monitoring, AI-based prediction, and optimization recommendations to help users make better decisions about their cloud resources. Instead of manually examining large amounts of billing information, the system presents important cost insights in a simple and understandable manner.

The experimental analysis demonstrates that the proposed approach can assist in identifying high-cost resources, unused resources, cost anomalies, and possible optimization opportunities. The dashboard further improves usability by presenting cost trends, resource-wise expenditure, predicted costs, and recommended actions through vi sual charts and summaries.

Overall, the AI Cloud Cost Optimizer can serve as a practical decision-support system for reducing unnecessary cloud expenditure while maintaining efficient resource utilization. In future work, the system can be enhanced with real-time cloud-provider integration, automated resource optimization, multi-cloud cost comparison, advanced cost forecasting, and AI-driven automatic recommendations.

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