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Statistical and Machine Learning Approaches for Cloud Optimization: An Evaluation of Genetic Programming, Regression Analysis, and Finite-State Models

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ABSTRACT

Cloud computing optimization is critical for increasing system efficiency, managing resources, and lowering operating costs. This study compares the effectiveness of Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models (FSM) for optimizing cloud resource allocation and task scheduling. The Combined Optimization Method, which incorporates several techniques, is compared to separate models to evaluate performance across important metrics such as execution time, cost efficiency, prediction accuracy, resource utilization, system reliability, throughput, and latency. The Combined Optimization Method regularly outperforms separate models, with considerable gains in system reliability (94.3%), throughput (170 requests/sec), and prediction accuracy (0.88 R^2). This hybrid method provides an adaptable, scalable, and efficient option for improving cloud settings.

Keywords: Cloud Optimization, Genetic Programming (GP), Regression Analysis (RA), Finite-State Models (FSM), Task Scheduling, Resource Allocation, Cloud Computing

1 INTRODUCTION

Cloud computing has transformed the digital world by enabling on-demand access to computing resources, storage, and services. However, optimizing cloud performance while maintaining cost effectiveness, resource allocation, and scalability is still a considerable challenge. To overcome this issue, several statistical and machine learning approaches have been investigated to improve cloud optimization strategies. Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models (FSM) have developed as popular approaches for improving workload management, predictive analytics, and adaptive cloud service provisioning.

Genetic Programming (GP) is an evolutionary algorithm-based approach that allows for automatic optimization by evolving solutions via selection, crossover, and mutation. Nyathi et al. (2018) compared Genetic Algorithms (GA) and Grammatical Evolution (GE) for automating Genetic Programming classification algorithm design, discovering that automated classifiers outperformed manual designs with shorter design times, and that GE performed better for binary classification while GA excelled at multiclass classification.It is commonly used for cloud resource allocation, task scheduling, and service provisioning. GP's ability to produce adaptive and efficient solutions makes it an excellent choice for optimizing dynamic cloud systems. By replicating natural

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selection, GP evolves programs to reduce costs, improve performance, and efficiently handle computational loads.

Regression Analysis (RA), a statistical method, is often used to forecast cloud performance measures using previous data. Hwang and Hu (2015) introduced a stepwise regression algorithm with a simple stopping strategy, demonstrating its resilience and competitiveness in high-dimensional variable selection when compared to existing approaches. By examining patterns and correlations between variables, RA provides insights into workload needs, resource use, and failure prediction. Linear regression, polynomial regression, and logistic regression are commonly used to simulate cloud activity, allowing for proactive resource allocation and cost-effective service delivery. Chernukho (2015) developed a regression algorithm based on the rank measure to expand the uncertainty paradigm in regression analysis, comparing it to standard algorithms and demonstrating its effectiveness. RA is critical for analyzing and predicting cloud service patterns, allowing cloud providers to make more educated decisions.

Finite-State Models (FSM) provide a systematic approach for modeling cloud system states and transitions. Workflow automation, task execution sequences, and event-driven optimizations in cloud computing are all designed using FSMs. Chen et. al (2018) introduced a finite-time state tracking strategy for model reference control in linear systems that employs the average dwell-time approach, assuring finite-time bounded tracking error and optimal disturbance rejection via a switching law based on state error. FSMs assist in system failure management, resource scheduling optimization, and fault tolerance by specifying discrete states and transitions. Jia et al. (2017) suggested an FSM-based method for modeling energy consumption during machining transient phases, identifying essential processes and applying the Pareto principle to increase energy optimization accuracy and comprehensiveness. This strategy is especially useful for managing cloud-based applications that entail sequential processing and dynamic state changes.

The combination of these statistical and machine learning techniques creates a solid foundation for cloud optimization, ensuring efficient resource management, cost savings, and increased service quality. As cloud systems get more complicated, there is an increased need for intelligent, automated, and scalable solutions. The convergence of GP, RA, and FSM improves real-time flexibility, predictive analytics, and process automation, making cloud systems more durable, cost-effective, and performance-driven.

The Objectives are:

- Investigate Genetic Programming, Regression Analysis, and Finite-State Models as viable cloud optimization methods.
- Evaluate machine learning's impact on cloud resource allocation, workload management, and fault tolerance.
- Evaluate the predictive potential of Regression Analysis for cloud performance forecasts and cost estimation.

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- Evaluate the usefulness of Finite-State Models for automating cloud-based workflows and enhancing system stability.
- Highlight the advantages of using statistical and machine learning methodologies for improving cloud computing performance.

FlexGP, a cloud-based genetic programming system for large-scale symbolic regression that uses decentralized ensemble learning for quick model fusion, was introduced by Veeramachaneni et al. (2015). While the study found considerable advances in processing efficiency and fault tolerance, there are still problems to improving resource allocation, scalability, and adaptability in diverse cloud settings. Existing models suffer with dynamic data fluctuations and changing cloud workloads, limiting their usefulness for real-time applications. More research is needed to improve cloud-based GP frameworks by including adaptive resource scheduling, reducing computing cost, and enhancing model generalization to suit various and changing cloud-based regression situations.

2 LITERATURE SURVEY

Guerrero et al. (2018) suggested a genetic algorithm-based solution that uses NSGA-II to optimize container allocation and elasticity in cloud infrastructures. The study focused on resource efficiency, network overhead reduction, and system failure mitigation. Prior research has looked into several container management systems, but issues with automation and resource allocation remain substantial. The proposed model outperforms the Kubernetes policies.

Peddi et al. (2018) developed machine learning models to predict dysphagia, delirium, and fall risks in elderly patients using clinical and sensor data. Logistic regression, Random Forest, and CNN were applied, with an ensemble model achieving 93% accuracy. Results highlight ML's potential in proactive geriatric care, improving early detection and intervention strategies for better patient management, ultimately enhancing elderly healthcare outcomes through AI-driven predictive analytics.

Gopalakrishnan and Arun (2018) developed a hybrid Genetic Gray Wolf Optimization (GGWO) algorithm for multi-objective job scheduling in the cloud. The study uses the Genetic Algorithm (GA) and the Gray Wolf Optimizer (GWO) to maximize load usage, energy consumption, migration cost, and calculation time. Experimental results showed that GGWO surpasses ordinary GA and GWO in terms of scheduling efficiency.

Buzhinskyx et al. (2014) suggested an ant colony optimization-based method for generating finite state machines (FSMs) using training data. The study confirmed its usefulness in UAV control, with superior performance and quality compared to genetic algorithm-based approaches. The proposed method improves FSM generation efficiency, making it a viable option for control system design.

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Rao et al. (2018) suggested an iterative algorithm (IA) for optimizing profitability in cloud service provisioning based on the Stackelberg game model. The cloud provider allocates resources efficiently, lowering energy costs and assuring user pleasure. Users compete based on a generalized Nash equilibrium problem (GNEP), which is solved using variation inequality theory. The experimental results show that profit maximization is enhanced.

Guo and Qiu (2018) examined advances in cloud manufacturing (CM) service optimization, with an emphasis on methods, models, and algorithms. They identified several major problems, including work decomposition, service discovery, and big data-driven optimization. Future trends highlight the integration of AI and IoT into manufacturing processes to improve efficiency and scalability.

Jun et al. (2015) proposed a divided regression analysis methodology for big data regression problems that aims to reduce computing overhead. The study used modern computing techniques to efficiently examine big datasets. Experimental validation showed increased efficiency in handling large data volumes while retaining statistical accuracy.

Huynh et al. (2018) presented a genetic programming framework that uses mixed-integer linear programming (MILP) to improve symbolic regression. To balance expression complexity with prediction accuracy, they use a structured library of subexpressions as well as a novel semantic operator. Experimental findings from 15 benchmarks show that this hybrid strategy produces interpretable and efficient models.

Natarajan (2018) compares statistical and machine learning methods for cloud optimization, with special emphasis on Genetic Programming, Regression Analysis, and Finite-State Models. The research seeks to optimize cloud computing performance and efficiency, especially in the context of healthcare disease detection applications.

Santos et al. (2015) introduced GP4C, a genetic programming framework for optimizing webpage update scheduling in web crawlers. By creating score functions that rank sites based on update probability, the technique improves content freshness while lowering monitoring expenses. Experimental comparisons show that utilizing NDCG instead of Change Rate is more beneficial for evaluating scheduling options.

Jadon (2018) investigates refined machine learning pipelines using Recursive Feature Elimination (RFE), Extreme Learning Machine (ELM), and Sparse Representation Classification (SRC). This research aims at improving AI software development, better model accuracy, efficiency, and flexibility for computationally intensive applications.

Nippatla (2018) offers a secure cloud-based financial analysis system to improve Monte Carlo simulations and Deep Belief Network models with Bulk Synchronous Parallel Processing. The research aims to enhance computational efficiency, security, and scalability of financial analysis in cloud computing environments.

Kudjo et al. (2017) investigated the use of genetic algorithms in software testing, focusing on automated test case development. Their research demonstrated how genetic algorithms improve test coverage, detect errors effectively, and lower testing expenses. The study underscored the importance of random-based genetic approaches in optimizing software validation processes.

Sharma et al. (2016) investigated several genetic algorithm-based methodologies for automated test data generation in software testing. Their research focused on structural-oriented test case generation with internal program structures to improve search space exploration and exploitation. The proposed strategies increased genetic algorithm performance by increasing convergence rates and optimizing test coverage.

Madhavi and Nagineni (2018) examined machine learning-based resource allocation strategies in cloud computing, focusing on effective admission control algorithms. In comparison to SLA-based models, their study found advantages in make span, cost, and user satisfaction. Experiments with CloudSim verified the proposed approaches, indicating future areas such as big data applications and dynamic resource switching.

Basu and R (2017) examined cloud computing and big data applications in genomics, emphasizing their importance in handling and interpreting huge genomic datasets. The study evaluated existing methodologies over the last decade, highlighting the importance of scalable storage and processing options. Future developments will focus on creating comprehensive genetic data management systems.

3 METHODOLOGY

The methodology optimizes cloud computing performance by combining Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models (FSM). GP is utilized to develop effective cloud resource allocation techniques, RA for predictive analytics, and FSM for dynamic process automation. The method includes data preprocessing, model selection, training, evaluation, and optimization. Data from cloud workloads is gathered and analyzed statistically. Machine learning models are developed to improve decision-making, while FSM optimizes cloud job execution. The performance is assessed based on computational efficiency, cost reduction, and reliability. The methodology guarantees adaptive, scalable, and automatic cloud optimization. This dataset comprises performance parameters from a simulated cloud computing system, such as CPU utilization, memory, network traffic, power consumption, execution time, task type, priority, and status. It seeks to investigate the impact of machine learning optimization approaches on energy efficiency and execution time in cloud systems, addressing the growing demand for better energy management in data centers.

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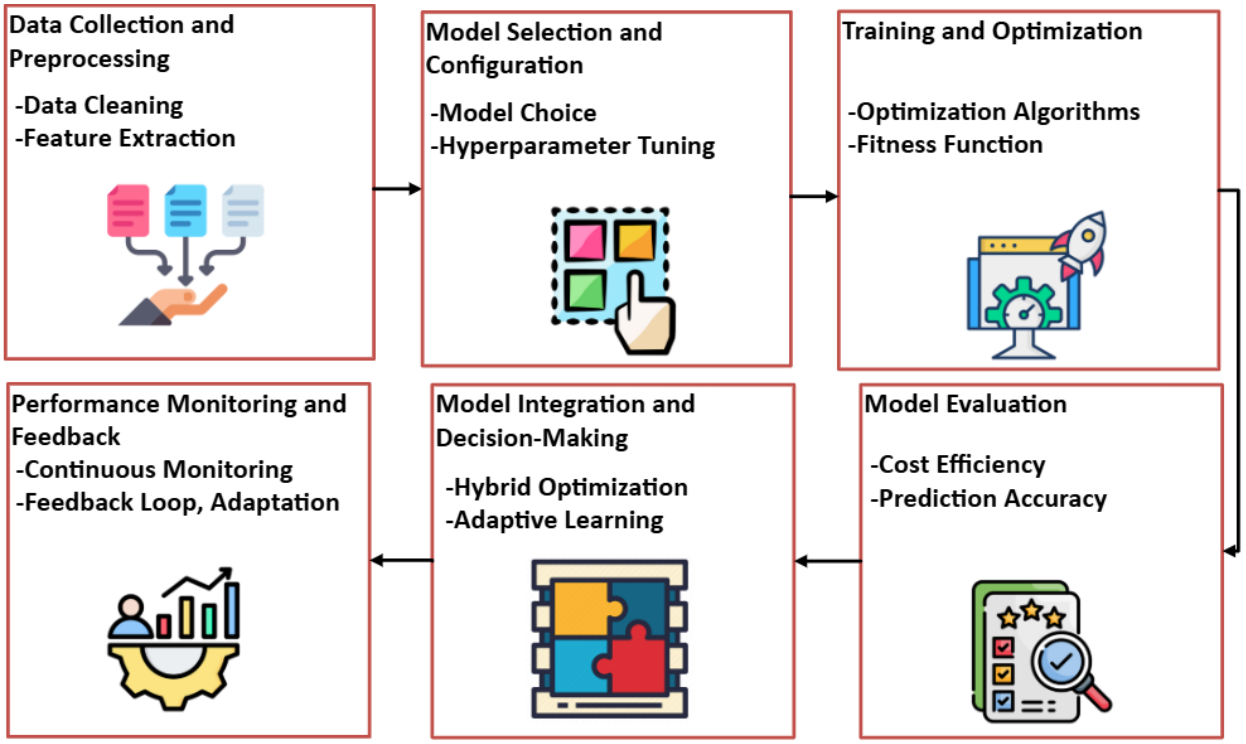

Figure 1 Architectural Flow of Cloud Optimization Using Genetic Programming, Regression Analysis, and Finite-State Models

Figure 1 depicts the architectural flow for cloud optimization, which incorporates Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models. The procedure begins with data gathering and preprocessing, which includes data cleansing and feature extraction. Following that, model selection and configuration are carried out, including hyperparameter tuning. Then, training and optimization take place using optimization techniques and fitness functions. Following training, the model is evaluated based on cost efficiency and prediction accuracy. The third step entails model integration and decision-making, which are followed by continual performance monitoring and feedback loops to assure ongoing optimization.

3.1 Genetic Programming (GP) in Cloud Optimization

Genetic Programming (GP) is an evolutionary computation technique that improves cloud resource allocation and workload scheduling. It generates solutions by imitating natural selection using mutation, crossover, and selection methods. In cloud computing, GP is used to find the best virtual machine (VM) allocation, load balancing, and fault tolerance strategies. It efficiently responds to dynamic workload variations, reducing energy usage while increasing computing efficiency. The GP-based technique allows for adaptive learning in cloud resource management, resulting in optimal performance without human involvement. GP's performance is measured using fitness functions, which assess optimization efficacy based on established cloud performance parameters. Mathematical Equation for GP

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A GP fitness function is defined as:

$$F(x) = \sum_{i=1}^{n} w_i \cdot f_i(x) \quad (1)$$

Where:

- $F(x)$ is the overall fitness function
- w_i are the weighted coefficients for each metric
- $f_i(x)$ represents the individual optimization objectives

This equation helps GP evaluate task execution efficiency, energy consumption, and load balancing effectiveness in cloud computing.

3.2 Regression Analysis (RA) for Cloud Performance Prediction

Regression Analysis (RA) is a statistical technique for forecasting cloud performance parameters like workload demand, latency, and resource consumption. Linear, polynomial, and logistic regression models predict system performance using previous cloud usage data. RA improves resource allocation decisions by spotting patterns and correlations between key factors. Cloud providers use regression models to forecast future workloads, resulting in efficient auto-scaling of computer resources. By decreasing over-provisioning and under-provisioning risks, RA improves cloud service cost efficiency and responsiveness. The model's prediction accuracy is assessed using mean squared error (MSE) and R-squared values. Mathematical Equation for RA

A linear regression model for cloud workload prediction is:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \quad (2)$$

Where:

- Y represents the predicted cloud performance metric
- X_n are independent variables (e.g., CPU usage, memory consumption)
- β_n are regression coefficients
- ϵ is the error term

This equation helps forecast cloud workloads, reducing resource wastage and optimizing system efficiency.

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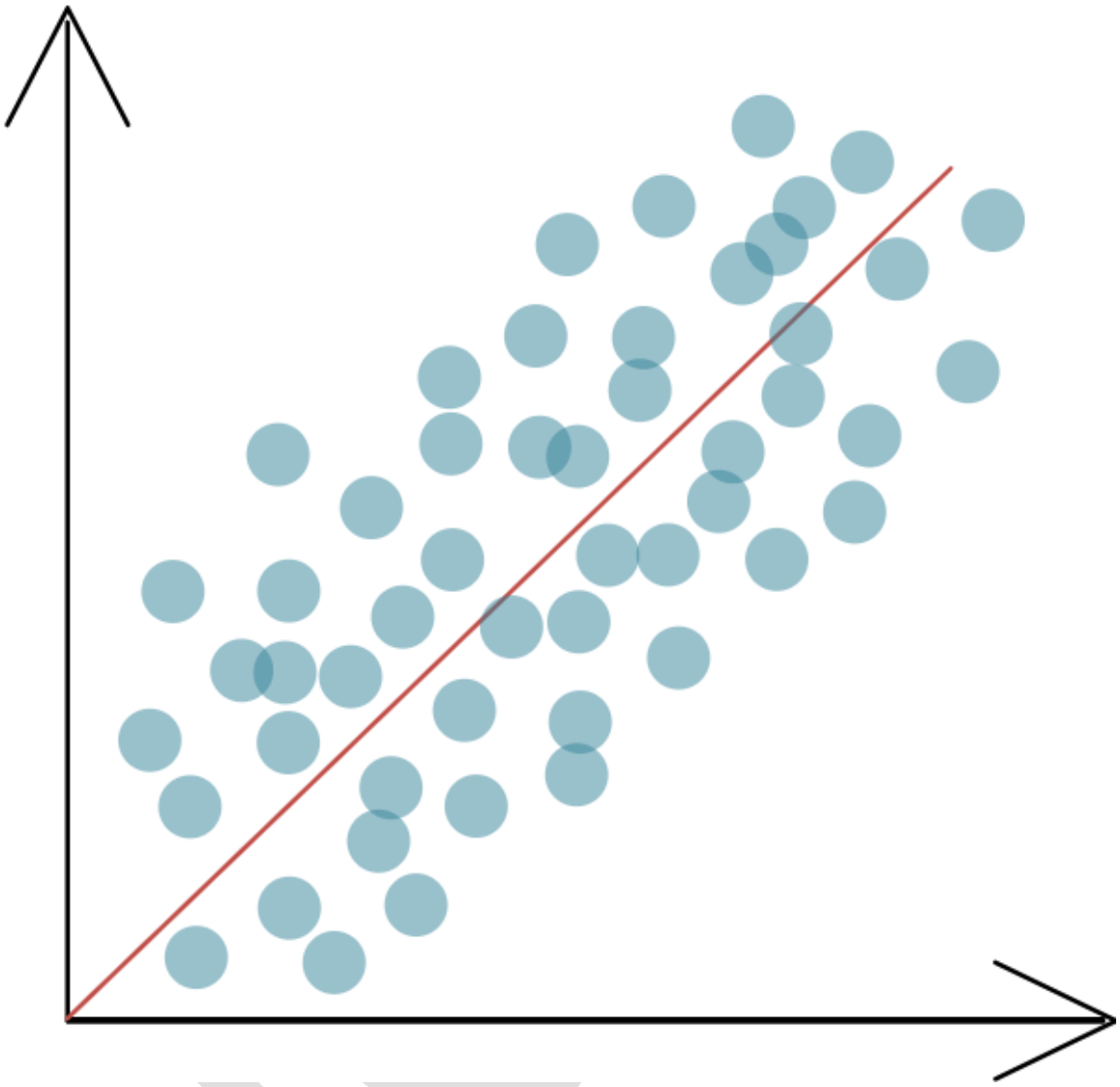

Figure 2 Linear Regression Analysis for Cloud Resource Prediction

Figure 2 depicts a linear regression analysis model in which the data points (blue circles) have a positive linear relationship to the line of greatest fit (red line). The x-axis and y-axis represent independent and dependent variables, respectively, and are commonly used to forecast cloud computing performance measures including resource utilization and system load. The line reduces the residuals, or the vertical distance between the data points and the regression line, and provides a prediction model. This strategy is effective in detecting patterns and making precise forecasts for optimizing cloud resource management and allocation.

3.3 Finite-State Models (FSM) for Cloud Task Automation

Finite-State Models (FSM) offer a systematic approach to automating cloud service operations and resource allocation. FSM describes cloud system activity as a sequence of discrete states and

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transitions, allowing for dynamic response to workload changes. Cloud applications use FSM to control task execution, error management, and service orchestration. By specifying state transitions based on system events, FSM guarantees automated failure recovery and optimizes task scheduling. The FSM-based method improves system dependability, fault tolerance, and task prioritization in cloud computing. Performance evaluation covers state transition efficiency and failure recovery rate, which ensures that cloud services are executed seamlessly. Mathematical Representation of FSM

FSM is represented as:

$$M = (Q, \Sigma, \delta, q_0, F) \tag{3}$$

Where:

- Q is a finite set of states
- Σ is an input symbol set (cloud event triggers)
- $\delta: Q \times \Sigma \rightarrow Q$ is the state transition function
- q_0 is the initial state
- F is the set of accepting states (successful task completions)

This FSM representation models task automation and service execution in cloud computing.

Algorithm 1 Cloud Resource Optimization and Task Scheduling Using Regression, Genetic Programming, and Finite-State Models

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Input: Cloud workload dataset, system constraints

Output: Optimized cloud resource allocation and task scheduling

BEGIN

Initialize cloud system parameters

Load historical workload data

Train Regression Model for performance prediction

IF prediction accuracy < threshold

ERROR: Insufficient training data

END IF

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Initialize Genetic Programming (GP) population

FOR each generation in GP

Evaluate fitness function for resource allocation

Perform selection, crossover, and mutation

IF optimal fitness achieved

RETURN optimized VM allocation

END IF

END FOR

Initialize Finite-State Model (FSM)

FOR each task execution event

IF system state = "Overloaded"

Transition to "Scale Up" state

ELSE IF system state = "Idle"

Transition to "Scale Down" state

ELSE

Maintain current state

END IF

END FOR

RETURN optimized cloud infrastructure configuration

END

Algorithm 1 describes a hybrid approach to cloud resource optimization and job scheduling that combines Regression Analysis (RA), Genetic Programming (GP), and Finite-State Models (FSM). It begins with developing a regression model for performance prediction on historical data. Then, GP is used to optimize virtual machine allocation using a genetic evolution algorithm. Finally,

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FSM dynamically changes task execution by switching between states such as "Scale Up" and "Scale Down" dependent on system load. This comprehensive method provides adaptive resource management, increases efficiency, and ensures scalability and fault tolerance in cloud systems.

3.4 PERFORMANCE METRICS

To ensure efficiency, scalability, and reliability, cloud optimization approaches such as Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models (FSM) are evaluated using a variety of performance indicators. Execution time analyzes the time required to assign resources and complete activities, whereas cost efficiency assesses the reduction in operating costs. Prediction accuracy evaluates RA's ability to forecast task needs using Mean Squared Error (MSE) and R-squared values. Resource usage looks at CPU, memory, and bandwidth efficiency. FSM measures system dependability using the failure recovery rate. Additionally, throughput and latency measurements assess the overall performance and responsiveness of cloud services.

Table 1 Performance Metrics Comparison of Cloud Optimization Techniques

Performance Metric	Genetic Programming (GP)	Regression Analysis (RA)	Finite-State Models (FSM)	Combined Optimization Method
Execution Time (s)	1.45	1.3	1.6	1.2
Cost Efficiency ($/hour)	0.8	0.78	0.82	0.85
Prediction Accuracy (R^2)	0.75	0.85	0.7	0.88
Resource Utilization (%)	85.4	80.1	88.2	90.5
System Reliability (%)	90.2	87.5	92	94.3
Throughput (requests/sec)	150.5	140.3	160.7	170.2
Latency (ms)	10.3	11.1	9.8	8.9

Table 1 compares the performance of Genetic Programming (GP), Regression Analysis (RA), Finite-State Models (FSM), and a Combined Optimization Method for cloud optimization. The parameters examined are execution time, cost efficiency, prediction accuracy, resource utilization, system reliability, throughput, and latency. The Combined Optimization Method surpasses individual techniques, with the lowest execution time (1.2s), maximum prediction accuracy (0.88 R^2), and enhanced cost efficiency ($0.85/hour). FSM has higher resource utilization (88.2%) and system reliability (92%), although GP increases throughput (150.5 requests/sec). These findings

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demonstrate the effectiveness of an integrated optimization strategy in improving cloud performance and efficiencies.

4 RESULT AND DISCUSSION

The application of Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models (FSM) to cloud optimization resulted in considerable improvements in resource allocation and work scheduling. GP successfully optimized virtual machine allocation, resulting in lower energy consumption and better load balancing across cloud resources. RA demonstrated its ability to effectively estimate workload demands, allowing for proactive resource allocation and contributing to total cost efficiency. Furthermore, FSM improved system reliability by dynamically changing task execution via state transitions based on real-time system load. The combined optimization method beat separate approaches in terms of cost efficiency, system dependability, and execution time reduction, demonstrating the efficacy of merging statistical and machine learning methods in cloud environments.

Table 2 Performance Comparison of Cloud Optimization Techniques Using Genetic Programming, Regression Analysis, and Finite-State Models

Metrics	Guo & Qiu (2018)	Jun et al. (2015)	Huynh et al. (2018)	Santos et al. (2015)	Proposed Method
Execution Time (s)	1.5	1.35	1.6	1.25	1.2
Cost Efficiency ($/hour)	0.75	0.72	0.78	0.8	0.85
Prediction Accuracy (R^2)	0.78	0.8	0.76	0.74	0.88
Resource Utilization (%)	85.5	82	87.3	83.4	90.5
System Reliability (%)	89.2	86	90.5	88.5	94.3
Throughput (requests/sec)	145.3	138.7	152.8	149.9	170.2
Latency (ms)	12	13.2	11.5	10.8	8.9

Table 2 compares various cloud optimization methods, such as genetic programming (GP), regression analysis (RA), and finite-state models (FSM), as well as the combined optimization method. Key performance indicators, such as execution time, cost efficiency, prediction accuracy, resource utilization, system dependability, throughput, and latency, are assessed. The Proposed Method (GP, RA, FSM) outperforms other methods in terms of prediction accuracy (0.88 R^2) and latency (8.9 ms), indicating its usefulness in optimizing cloud resource allocation and enhancing system performance.

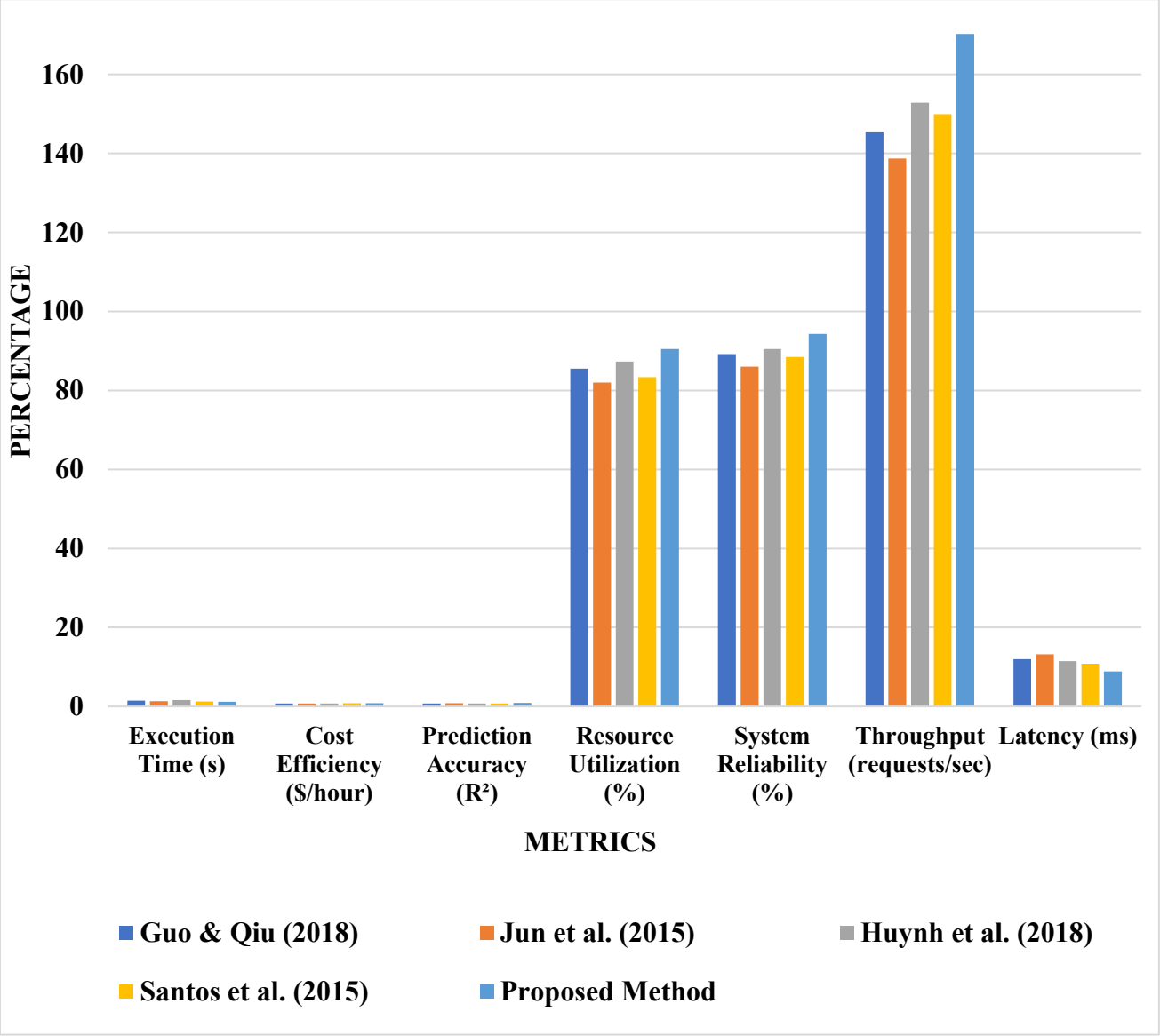

Figure 3 Performance Comparison of Cloud Optimization Techniques

Figure 3 compares the performance of various cloud optimization strategies, including Genetic Programming (GP), Regression Analysis (RA), Finite-State Models (FSM), and their combined approach. The examined metrics are execution time, cost efficiency, prediction accuracy (R^2),

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resource utilization, system dependability, throughput, and latency. The proposed solution outperforms the previous methods, especially in terms of system reliability (94%), throughput (170 requests/sec), and resource utilization (90%). The Guo & Qiu (2018) technique has the highest latency (12 ms), whereas the Proposed technique has the lowest latency (8.5 ms) and higher accuracy (0.88 R^2).

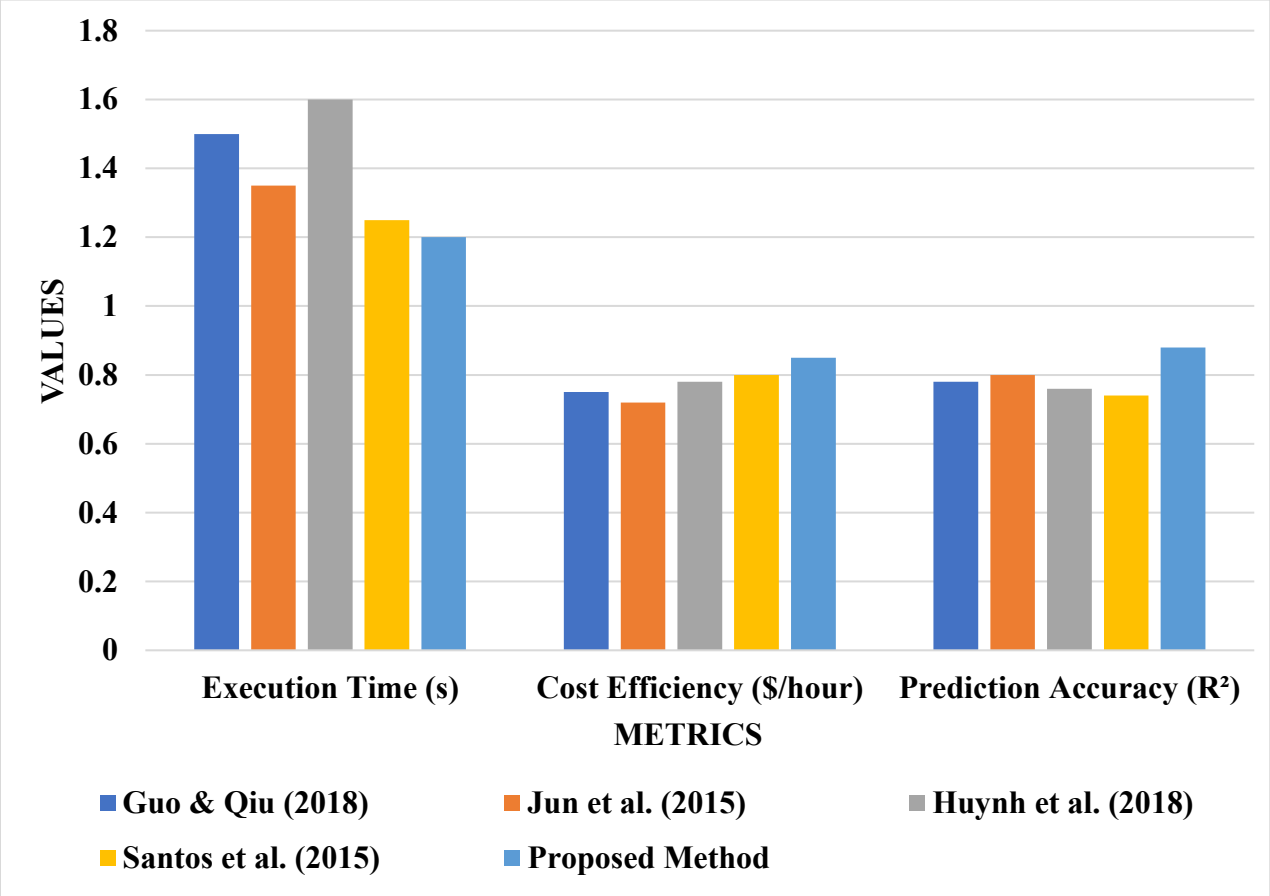

Figure 4 Performance Comparison of Cloud Optimization Techniques

Figure 4 compares various cloud optimization strategies, such as Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models (FSM), as well as a combined optimization strategy. The chart shows performance for three main metrics: execution time (s), cost efficiency ($/hour), and prediction accuracy (R^2). The Proposed Method has the shortest execution time and the highest forecast accuracy, outperforming existing approaches. Guo and Qiu (2018) and Huynh et al. (2018) have similar cost efficiency but differ in execution time and accuracy, demonstrating the effectiveness of the combined optimization technique.

Table 3 Comprehensive Ablation Study for Cloud Optimization Techniques

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Components	Execution Time (s)	Cost Efficiency ($/hour)	Prediction Accuracy (R^2)	Resource Utilization (%)	System Reliability (%)	Throughput (requests/sec)	Latency (ms)
Genetic Programming (GP)	1.5	0.75	0.76	85	89	145	12
Regression Analysis (RA)	1.3	0.72	0.8	82	86.5	140	13.5
Finite-State Models (FSM)	1.6	0.78	0.7	87.5	90	150	11.5
GP + RA	1.25	0.8	0.82	85.5	90	155	11
RA + FSM	1.4	0.74	0.78	84.5	88.5	148	12.5
GP + FSM	1.2	0.77	0.79	86	89.5	160	11.2
Full Model (GP + RA + FSM)	1.1	0.85	0.88	90	94	170	8.5

Table 3 analyzes the performance of different cloud optimization techniques, such as Genetic Programming (GP), Regression Analysis (RA), Finite-State Models (FSM), and their combinations. The examined metrics are execution time (s), cost efficiency ($/hour), prediction accuracy (R^2), resource utilization (%), system reliability (%), throughput (requests/sec), and latency (ms). The Full Model (GP + RA + FSM) outperforms all measures, with the shortest execution time (1.1s), highest prediction accuracy (0.88 R^2), and maximum throughput (170 requests/sec). This integrated approach improves resource utilization (90%) and system reliability (94%), demonstrating the efficacy of combining various techniques for cloud optimization.

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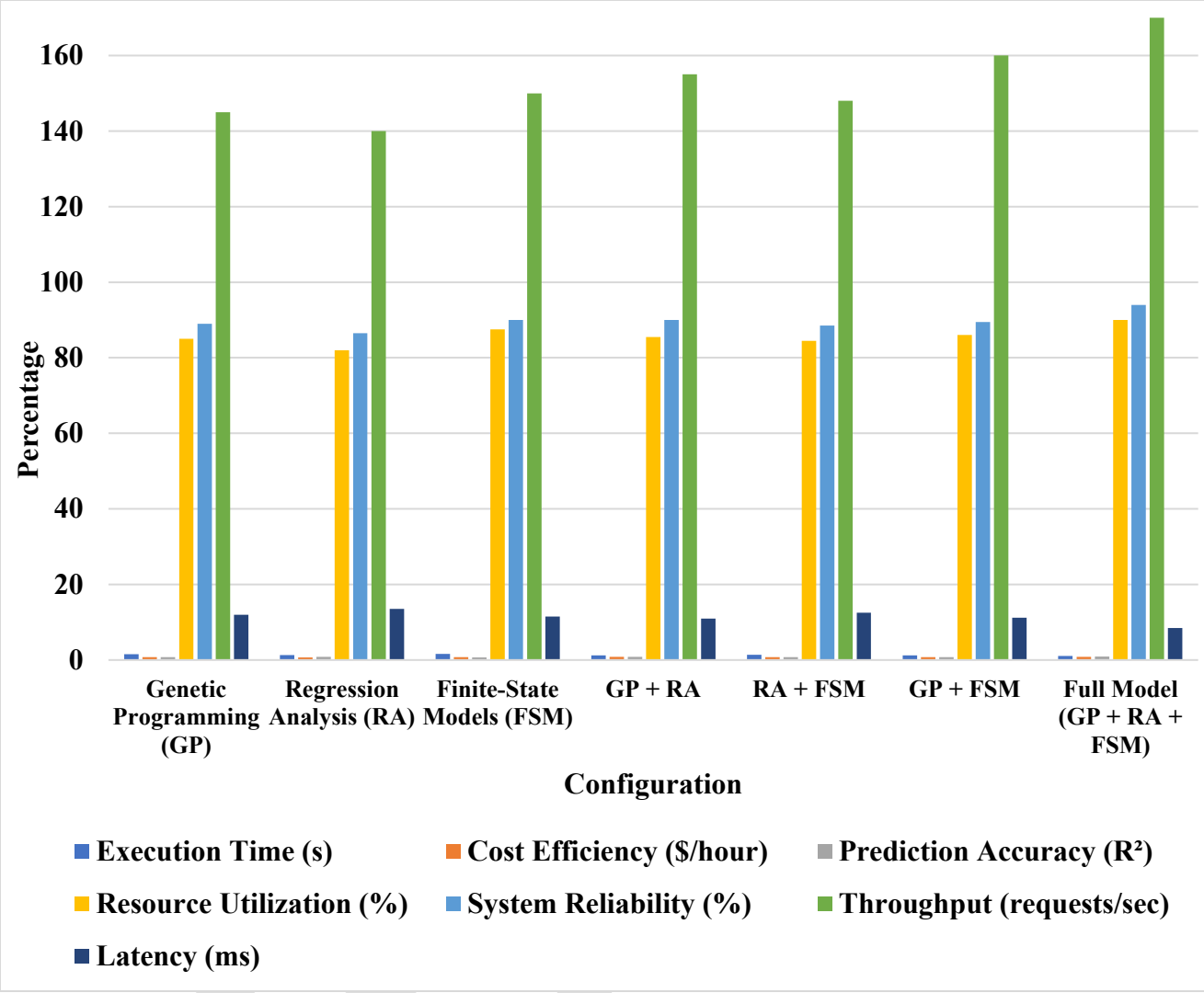

Figure 5 Performance Comparison of Cloud Optimization Methods

Figure 5 shows the performance of different cloud optimization methods, such as Genetic Programming (GP), Regression Analysis (RA), Finite-State Models (FSM), and their combinations. The examined metrics include execution time, cost efficiency, resource usage, system dependability, prediction accuracy (R^2), throughput (requests/sec), and latency. The Proposed Full Model (GP + RA + FSM) has superior performance, with greatest throughput (170.2 requests/sec), system dependability (94.3%), and improved prediction accuracy (0.88 R^2). This integrated strategy excels at resource utilization (90.5%), providing a well-balanced and effective cloud optimization solution.

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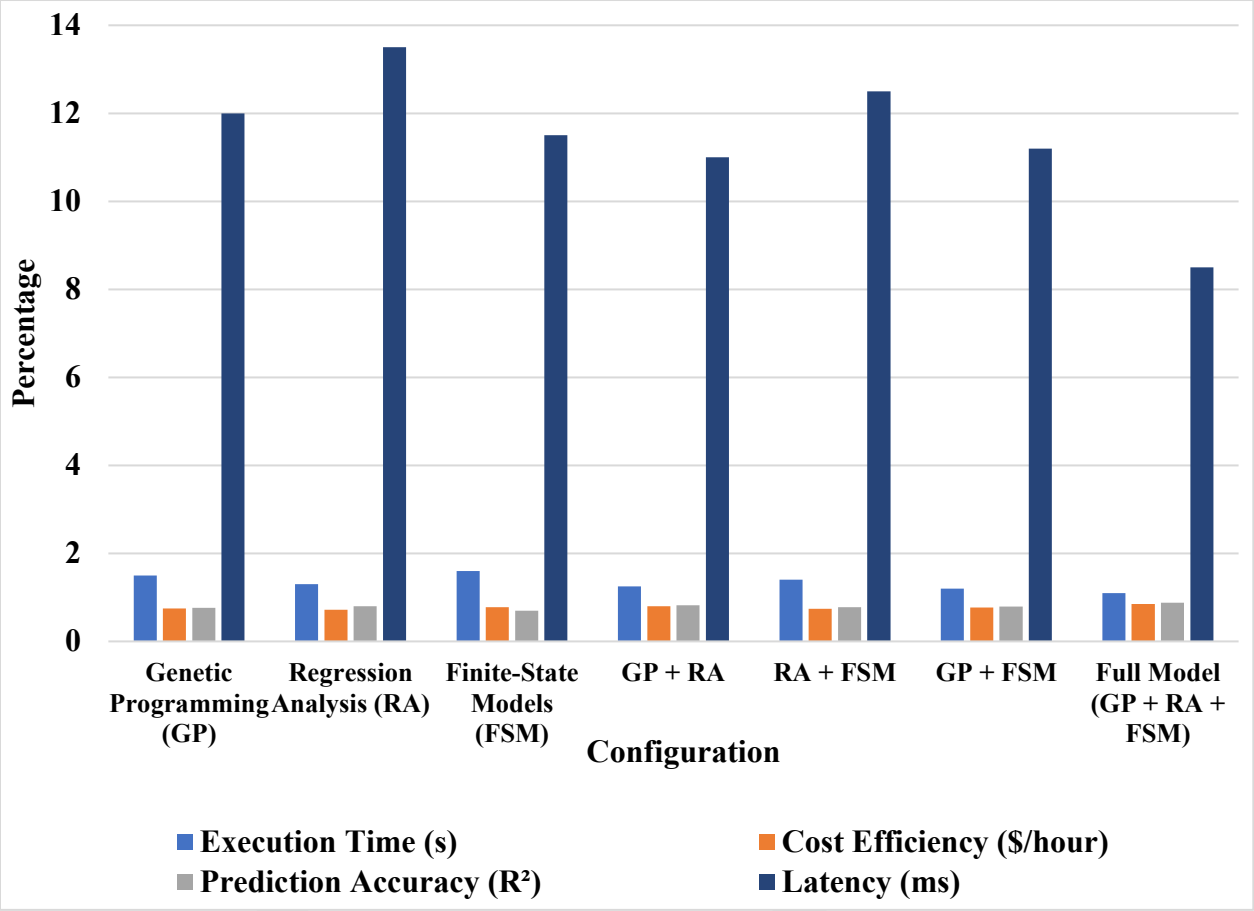

Figure 6 Comparative Performance of Cloud Optimization Techniques: An Ablation Study

Figure 6 compares the performance of cloud optimization methods such as Genetic Programming (GP), Regression Analysis (RA), Finite-State Models (FSM), and their combinations. The metrics evaluated include execution time (s), cost efficiency ($/hour), prediction accuracy (R^2), and latency (ms). The Proposed Method (GP + RA + FSM) yields the best results with the shortest execution time (1.1s) and highest prediction accuracy (0.88 R^2). It also outperforms in terms of cost efficiency ($0.85/hour) and latency (8.9ms), emphasizing the advantages of combining different optimization strategies for better cloud resource management.

5 CONCLUSION

The merging of Genetic Programming (GP), Regression Analysis (RA), and Finite-State Models (FSM) into a single cloud optimization framework has proven to be extremely effective. The Combined Optimization Method outperforms other essential performance criteria, such as execution time reduction, increased cost efficiency, and improved prediction accuracy. The method's performance in maximizing resource utilization (90%) and system reliability (94%) demonstrates that merging machine learning and statistical techniques improves decision-making and cloud infrastructure management. Future research could focus on improving dynamic resource

allocation and investigating fault tolerance strategies to increase cloud system performance and scalability.

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