An Intelligent Framework for Flavor Recommendation and Cost Optimization in Hybrid Cloud Autoscaling

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Abstract

This research presents a flavor recommendation framework that intends to be used in hybrid clouds to address resource provisioning and cost issues. A cloud "flavor" is an instance type that assigns values for CPU, memory, storage, and networking. Today the flavor selection process is manual, and no dynamic technique is used, therefore, the process is inefficient because some flavors are underutilized. The proposed framework also provides flavor recommendations for autopiloted dynamic capacity provisioning using predictor analysis of workload and cost proportional to different CSPs. It uses an RNN_LSTM-based Proactive Predictive Engine (PPE) to quantitatively estimate future resource requirements and a Recommendation Engine consisting of the scoring and flavor engines. This framework receives the application's actual and predicted consumption of CPU and memory, cost fluctuations, and CSPs' options and then the selection of various flavors is performed in the runtime. Metrics are gathered, stored, and analyzed in real-time through Telegraf, InfluxDB, and Apache Libcloud for current resource allocation. Experimental results of the system on AWS and OpenStack show the benefit of using the proposed framework, which reduced the number of EBS and VMs by 19% and the cost saving by up to 17% compared with traditional and reactive approaches. This solution turns static resource allocation into a real-time predictive accuracy of how resources are best utilized as well as the expense at the hybrid cloud environment.

Keywords: Autoscaling; Flavor Recommendation; Hybrid Cloud; RNN_LSTM; RPE; CSPs; VMs; Cost optimization; Resource forecasting; CPU utilization; RAM utilization; InfluxDB, Telegraf; Apache Libcloud; Dynamic resource allocation

1. Introduction

Cloud computing service delivery has drastically changed the way Companies and organizations adapt and deploy their computational assets. As organizations' need for a more flexible solution to their infrastructure increases, the concept of hybrid cloud knew comes out as the transition between public and private clouds. This method can help organizations take advantage of both worlds and meet reasonable costs for their [1] effective work, number of resources, and data protection. In this regard, the notion of flavors that characterize configurations of computing elements including CPU, memory, storage, and networking are central to matching infrastructure capabilities with the demands of the applications.

The CSPs provide a wide variety [2] of Flavors designed to address a wide spectrum of application requirements, ranging from CPU-bound, memory-bound; or network-bound. This is compounded by the fact that different CSPs do not follow standard rules set down in defining the Flavors and their configuration. As mentioned above, the choice of the most appropriate Flavors might be considered as wandering through various criteria, different and [3] disjointed at the same time, different Flavors vendors and unpredictable dynamic workload requests, and manual selection of these Flavors have reported to be a tedious and an inefficient task.

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These resources therefore show that there is effectiveness in the proper selection of the right Flavors as they determine resource utilization and operating costs. The applications that run on hybrid cloud environments typically [4] experience a variable demand for computing resources that cannot always be predetermined and stationary. In the past, selecting the Flavors was frequently done based on the current workload or some pre-defined standardized [5] configuration. Once a particular taste is selected, it is often utilized again, even if its demand has not changed, which leads to inefficiency in resource use or over capacity in some instances. The static approach in question not only elevates operation costs but also the scale potential of clouds, which is thought of as one of the major benefits of hybrid environments.

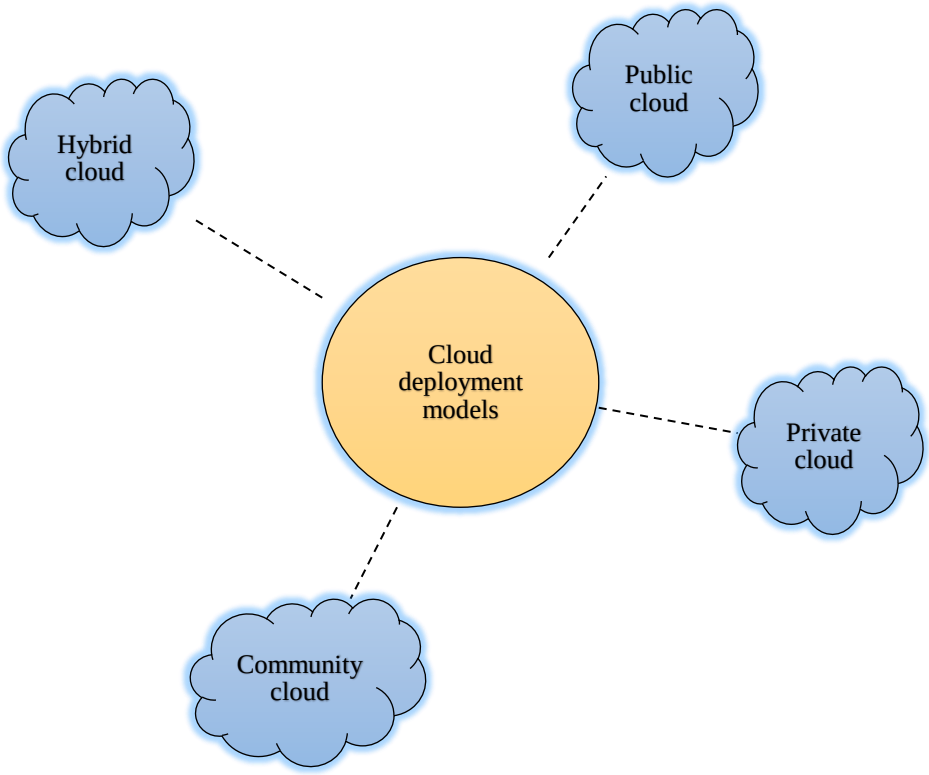

Figure 1. Deployed cloud models

To overcome these issues, contemporary cloud systems are implementing superior techniques for the allocation of resources and costs. Workload prediction and forecasting are included in such methodologies. They employ forecasting [6] of resource usage to determine future requirements if existing cloud structures are to be optimized. Thus, organizations obtain balanced and economical usage of cloud resources by provisioning them according to the expected demographic workload.

Of the mentioned predictive techniques, the machine learning (ML) as well as deep learning approaches for instance Recurrent Neural Networks (RNN) and [7] Long Short Term Memory (LSTM) networks contain many potentials. These models are particularly good at dealing with time series data and therefore provide a good testing ground for cloud resource usage data for analysis and predictions. Building on these capabilities, cloud systems can go from being simply reactive systems to proactive systems that can guarantee that resources are utilized exactly at the right time and place.

The fact that the work is done within the framework of autoscaling additionally enhances the possibilities of predictive methods. Autoscaling is [8] a process of automatically eliciting the required number of VMs or some other resources at a moment's notice depending on the demands. This process usually includes increasing resources in terms of capability during high demand rates and decreasing during low demand rates. Despite being a popular concept today autoscaling is a complex process whose reliability depends on the accurate prediction of workloads and the ability to allocate [9] resources. The problem with resource prediction and flavor selection not being exact to a tee means that autoscaling may lead to a wastage of resources or having to do away with the services.

Another area of importance in the choice of Flavors is cost reduction, together with prediction and autoscaling. The pricing of the cloud resources depends on the CSPs and the number of VMs, the types of Flavors, and the

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time for which the resources are [10] employed. In cases where multiple CSPs or CSPs and internal resources are used, knowledge of cost anomalies and how to manage them is essential. In other words, organizations must measure the relative advantages of the different trade-off options to find the most cost-effective solution for their situations and uses.

In addition, the intensification of cloud services makes it even more challenging to select the proper Flavors. [11] CSPs often add new services to their portfolios and change the prices for existing ones. It is important to be aware of such changes to manage resources efficiently; however, such a task would be cumbersome to accomplish manually. As is the case in hybrid cloud systems, this becomes complex as the administrators have to evaluate [11] and compare the solutions across the different providers.

The need to have automated intelligent systems to deal with these issues is thus apparent. When workload forecast, auto-scaling, and cost optimization are incorporated into such systems, they can help to keep the choice [12] of Flavors simple while achieving the best results. Such systems must also include real-time data tracking capability to make sure the recommendations it is providing are fresh in dynamic cloudy conditions.

The precise determination of workloads and the suggestions about relevant Flavors have significant implications for the nature of cloud computing. It helps organizations to get the maximum benefits of these hybrid cloud models, flexibility, reliability, and cost optimization. Also tends to decrease the workload of the administrators as they have more time to perform important tasks. This means that as cloud adoption becomes widespread in many industries, the demand for such intelligent systems will be well emphasized.

Therefore, Flavor selection is one of the critical requirements of cloud resource management; this is especially true in a hybrid cloud architecture. [13] The way workload prediction and autoscaling are applied, as well as cost recovery strategies determines the effectiveness of the strategies to select Flavors. Addressing the issues related to manual and static strategies, only the automated systems that can integrate top-notch efficient prognosis algorithms with cost-effective mechanisms might determine the way various organizations use the cloud. These developments represent further progress toward realizing the full potential of cloud computing – resource elasticity, scalability, and smart resource usage.

2. Related Work

A literature survey remains an important foundational tool in academic research, as it opens up for a researcher to engage deeply with the content of the selected field. Apart from synthesizing the current body of knowledge, the survey [14] also identifies shortcomings and recommendations for future research derived from the examined investigations. This process acts as the foundation of scientific advancement, which means that none of the new studies repeats the same effort as done by previous ones.

In its broadest sense, the art of a literature survey is based on the provision of a narrative of the field of study. In this way, when the researcher critically appraises and integrates the available research articles, one may find patterns, disparities, [15] and trends. Consequently, despite the methodological limitations of this synthesis, it gives a broad vision of the state of the field and the dynamics that led to its current development. As well as deepening the comprehension, this step highlights what is yet unknown or has been an object of a dispute, which defines the further focus of a researcher as on the value adding.

A good literature survey aims at providing extensive and systematic research into the literature of the topic of study. This [16] entails finding scholastic materials from both peer-reviewed and scholastic databases including journals, conference proceedings other sources such as books, and other online sources. Inclusion and exclusion criteria are used to determine which criteria are relevant and of high quality for selection. Identified sources are examined closely to make possible extraction of essential information including research objective, method, findings, and conclusions among others.

The discussion in a literature review is more than merely describing. It [17] only involves an assessment of the merits, demerits, and sources of bias of past research done in the same line. For example, the researcher may assess the quality of methods in prior research, and the sufficiency of data and reasonable for the analysis and findings. This evaluative process not only provides good insight into the field but also justifies the need to carry out the proposed research.

From a literature survey, [18] one of the identifiable benefits is the recognition of the areas that require research. They may appear in the form of areas that have not been addressed, discrepancies in the results or there being limitations to the techniques used. That is why, having described these gaps, the survey opens the possibility of further empirical investigations that can fill those gaps. For example, a field that tends to work with theoretical models might call for empirical support, or a field that has many short papers might benefit from long papers.

Moreover, a literature survey can be of great importance as [19] regards to setting of the proposed research. While positioning the study in the context of academic literature, the survey defines its relevance and

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contribution. This contextualization thus shows how the research meets a need in not only theory development but also in providing a potential solution to a real-life phenomenon. It convinces the peer, [20] the reviewer, and any other stakeholder because the research should matter and how it contributes to the body of knowledge.

It is also noteworthy that a literature survey can affect the methodological setting of a given research in addition to setting the context for the study. From the previous works, the researcher can identify which methods correspond to the objectives and which ones are those that have not been used and should not be repeated. For example, a literature review of predictive modelling in cloud computing might find that the previous literature relies on a specific set of methods that are predominantly based on machine learning; this then [21] implies the possible directions for improvement of that technique or the extent of leveraging an alternative method.

Conducting a literature survey is part of the continuous process of conducting academic research as more sources are discovered along the journey. It does not start only from the beginning of the study but develops together with it enhancing and expanding the knowledge of the researcher as new works appear. [22] This makes the research continuous in that it draws knowledge from the current progressing knowledge in the area.

Thus, a literature survey is not only the mere preparation stage in the research but is much more than that. An essential process that forms the [23] foundations and potentiality of a study, amplifying the success of the study, while giving the researcher direction during the research process. By providing a critical evaluation of the literature it defines the context for research, guides the search for opportunities to innovate and it makes the best use of the state of knowledge as a foundation for [24] the generation of new knowledge.

3. Objectives of the Research

Resource orchestration in the host environments of hybrid clouds is central to more efficient delivery of performance and costs. This research aims to solve the existing issues of the flawed, passive, and time-consuming selection of Flavors by the creation of a dynamic predictive model. They include self-service Flavors recommendation and workload prediction, which together with cost reduction on the one hand and general efficiency of used resources on the other hand.

- Design a low-cost architecture for recommending Flavors to improve resource management in hybrid-cloud platforms.
- Embed workload prediction by applying RNN_LSTM to predict the application resource needs properly.
- Please compare and evaluate the quantitative and qualitative enhancements of the cost and performance by making use of the proposed framework against the conventional Flavors selection approach.

4. Inspiration for Research

This implies that resource provisioning in the growing and complex hybrid cloud environments can only be solved by intelligent techniques. Reusable and carousal taste wheel techniques that have been used in the past are not very efficient, can waste materials, and time and cause extra expenses. This work is inspired by the desire to propose an automated solution that integrates workload forecasting and cost modelling to suggest the most suitable Flavors to support scalable, high performing, and cost-effective cloud systems in dynamic environments, and offset the drawbacks of current methods.

5. Developed Methodology

It is recommended that a flavor recommendation system be developed to suggest a flavor that is cost-efficient for the anticipated workload to ensure auto scaling. The Proactive Predictive Engine (PPE) and the Recommendation Engine are the two main parts that make up this system. Two parts make up the recommendation engine. These are the scoring engine and the taste engine as well. With the help of RNN_LSTM, the PPE makes projections on the future need for CPU resources. According to the predicted and actual consumption of the central processing unit (CPU), the scoring engine will calculate the necessary quantity of resources. Among the registered public and private cloud service providers, the flavor engine is the one that is tasked with determining the most suitable flavor. As shown in Figure 1, the essential elements that make up the flavor recommender that has been suggested are depicted.

The Metric Collector is a module designed to collect real-time usage metrics on system resources like CPU, RAM, etc out of virtual machines. It uses tools such as Telegraf, which is based on plugins to directly gather performance metrics. These metrics are important in predicting workload requirements and are passed to the Metric Storage system.

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The Metric Storage database is used to store all collected metrics for analysis. Platforms like InfluxDB contain metrics of time series data including usage of CPUs and RAM to support querying and predicting. PEC is supported and history workload data that is used to predict resources is stored in this repository.

PPE is the forecasting module of the program that utilizes RNN-LSTM models to predict future resource requirements (CPU, RAM). It analyses metrics held in Metric Storage and predicts the extent of workload needed over a given period. These predictions are provided to the Scoring Engine to determine resource usage calculation.

The Message Queue is specifically used to allow different modules of the framework to communicate with one another immediately. It utilizes third parties such as RabbitMQ for scheduling tasks, updates, and inter-module communication. This frees module dependencies and enhances scalability and tolerance in case of a failure.

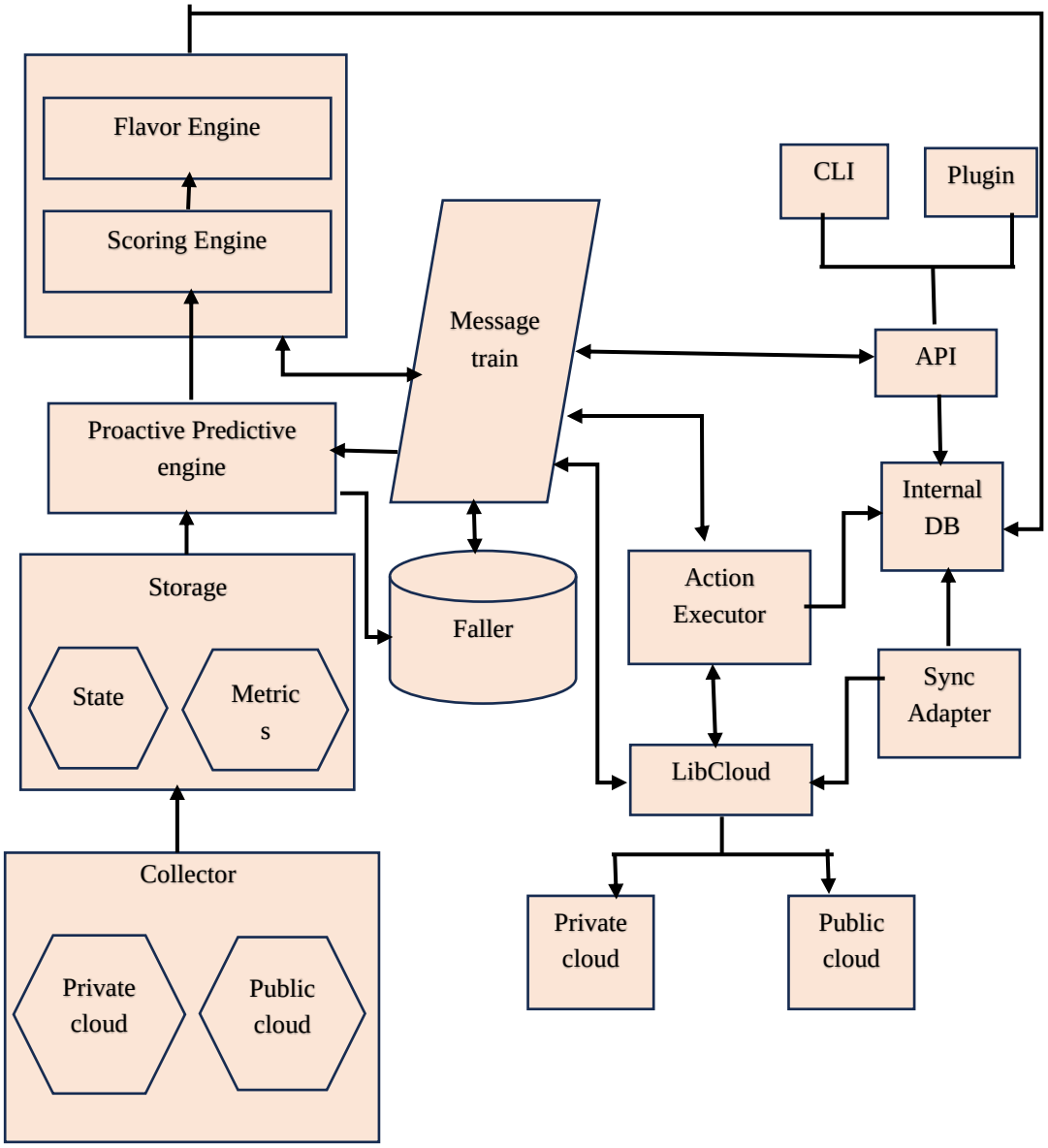

Figure 2. Illustrations of Flavor Recommendation Framework

The API refers to the set of calls that might be used by any application outside the framework to interact with it. By incorporating REST-based Services it provides an interface by which users can manage, monitor, and control the flavor recommendation system using a command line tool or GUI interface.

The Recommendation Engine makes decisions, which are then implemented by the Action Executor. In this way, it either provisions resources or changes configurations through interaction with the internal database and other

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modules. It is achieved through well-proven tools such as GoCD to guarantee execution integrity and in case of task failure; the tools support the rollback mechanisms to be initiated.

Libcloud is a Python library offering a unified API for interacting with multiple cloud providers in hybrid cloud environments. It fetches up-to-date flavor details, VM specifications, and provider configurations, streamlining multi-cloud management.

It is an internal key-value database, which has information about the resources of available cloud providers, the user templates, and other flavor history information. Thanks to the external cloud connectivity, it is designed to allow real-time selection of the three flavors and stores important operational information.

The Sync Adapter makes certain that the framework uses the most up-to-date information with cloud providers. With APIs and tools such as JAM Scheduler, it obtains new VM configurations, Flavors, and Costs and bulk this into InternalDB for the same to be filtered and recommended.

5.1 Scoring Engine

The Scoring Engine has been developed as a functional part of Flavor Recommendation Framework that is aimed at determining the number of resources (VCPUs and RAM) needed in further work based on PPE's forecast. From our experience, it also helps to avoid over- scaling or under- scaling the use of resources hence making it possible to balance resource scaling at an optimum level using Virtual Machines (VMs).

The engine performs three main functions:

- Makes averaging of CPU and RAM usage for the given time span.
- Calculates the number of minimum and maximum VCPUs and RAM required starting the workload taking a threshold and a buffer into consideration.
- Transmits these computed requirements to the Flavor Engine, from which the best flavor is chosen from the various cloud choices.

The mean of the CPU utilization in a certain prediction duration. This value represents the utilization factor derived from previous work, which is used to establish the basis for future requirements.

$$\mu = \frac{1}{t}\sum_{k=1}^{t} CPU\ u_k \quad (1)$$

The minimum provision of virtual CPUs necessary to achieve the expected mean CPU usage, constrained with reference to a given limit for allowable CPU usage.

$$VCPU_{min} = \left[\frac{\mu}{Threshold}\right] \quad (2)$$

The highest possible number of allotted virtual CPUs multiplied by the coefficient considering possible workload increases. This avoids under investment that is common during crisis and high needs.

$$VCPU_{max} = VCPU_{min} + \beta \cdot VCPU_{min} \quad (3)$$

Calculated depending on the average RAM utilization and proportional to the available resources.

$$RAM_{required} = \mu \cdot RAM_{available} \quad (4)$$

Number of required VCPUS + Number of required RAM · Price per each VCPU · Price per each unit of RAM = Total cost to provision the amount of VCPUS and RAM as envisioned for the forthcoming workload.

$$Cost_{total} = VCPU_{needed} * Price\ per\ VCPU \quad (5)$$

Where t = number of intervals, CPU u_k = CPU usage in interval k, μ = mean utilization, Threshold = confirms no overloading, β = buffer factor.

Algorithm 1: Scoring Engine

Step 1: Input forecasted CPU/RAM consumption.
Step 2: Calculate the average of the utilization over the short, medium and long prediction intervals.
Step 3: To calculate VCPU_min, use the said threshold.
Step 4: Define the addition of a buffer to form VCPU_max.
Step 5: Submit the results where the system identifies the best flavors to be used to the Flavor Engine.

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The Scoring Engine ensures scalability since it takes a measure of the reallocation of resources based on antecedent clamor.

5.2 Flavor Engine

The investigation carried out in this research indicates that the Flavor Engine is a sub-module of the Recommendation Engine in the Flavors Recommendation Framework. Its main application is to find the best flavor, which means a combination of CPU, RAM, and cost, given a list of cloud providers based on the forecasted demand. This is made possible through assessing the inputs from the Scoring Engine such as the number of VCPUs needed and the memory-RAM. With this data, the Flavor Engine communicates directly with InternalDB, which stores the updated flavor information (costs, specifications) of different cloud providers.

The Flavor Engine is cost effective and resource sufficient. It evaluates available flavors based on several criteria: total cost, number of VMs required, logical distribution of resources etc. To this end, when integrating a flavor selection algorithm, it first selects the most efficient flavor while considering workload requirements during auto scaling periods.

This defines total number of virtual machines (VMs required to meet the expected resource requirements). The average of the one equals total required VCPUs divided by VCPUs per flavor of all one instances to balance the workload between VMs.

$$VM_{required} = \frac{VCPU_{needed}}{VCPU_{Flavor}} \quad (6)$$

This gives total cost of provisioning the required number of VMs on the required flavor. That serves to increase the value of the total number of VMs for that specific flavor by the cost per VM for that flavor, which benefits the analysis of cost structure.

$$Cost_{Flavor} = VM_{Required} * Price_{Flavor} \quad (7)$$

The anticipated consumption of RAM as well as the number of virtual machines determine the overall amount of RAM that is needed:

$$RAM_{total} = VM_{required} * RAM_{flavor} \quad (8)$$

One measure that may be used to assess the cost-effectiveness of a flavor depending on the distribution of its resources is:

$$CE_{flavor} = \frac{VCPU_{flavor} + RAM_{flavor}}{Price_{flavor}} \quad (9)$$

The proportion of virtual machines (VMs) that are necessary for a flavor in comparison with different flavors for a comparable load:

$$VAR_{flavor} = \frac{VM_{required}}{VM_{total}} \quad (10)$$

To guarantee that a flavor can adapt to the needs of the workload:

$$RSC_{flavor} = VCPU_{needed} \leq VCPU_{flavor} \; and \; RAM_{needed} \leq RAM_{flavor} \quad (11)$$

Compares the prices of different tastes in order to emphasize the savings:

$$\Delta C = Cost_{flavor1} - Cost_{flavor2} \quad (12)$$

Algorithm 2: Flavor engine

Input: , VCPUs as per scoring engine, RAM as per scoring engine, flavor_details, flavour details databases

Output: Optimal flavor details

Step 1. set min_cost initially is infinity, optimal_flavor is none

Step 2. For each cloud provider:

a. Select flavors from flavor_details

b. For each flavor:

Calculate VMs required: VM_required = round up of division of VCPU_needed with VCPU_flavor

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Compute total cost: Cost_flavor = VM_required * Price_flavor

c. Compare total cost:

If the current cost_flavor is less than min_cost set the min_cost equal to cost_flavor and set the optimal_flavor to the current flavor.
If costs are the same, go for the flavor that has less number of VMs but more VCPUs

Step 3. Insert the optimal_flavor in Recommend_Flavor table

Step 4. Return data of optimal_flavor such as name, VCPU, RAM and cost.

The Flavor Engine helps to guarantee that the selected flavor will do so at the least cost possible in order to meet forecasted needs. It is integrated into the Recommendation Framework to provide the capability of resource provisioning for hybrid cloud infrastructure.

5.3 Optimized Recommendation Engine Algorithm

The Optimized Recommendation Engine Algorithm is a recommendation system developed to advise the most price efficient flavors for expected workloads in a hybrid cloud. The WDE information is called up either from the PPE, or from calculations performed by the Scoring Engine and the Flavor Engine to settle on the proper flavor.

This algorithm operates in the following key stages:

- Prediction Input: In case of the PPE, the CPU and the RAM utilization within the next time steps are forecasted by using the RNN-LSTM models with the historical data. The utilization as forecasted constitutes the input to the Scoring Engine.
- Resource Requirement Calculation (Scoring Engine): The Scoring Engine uses the predicted workload to calculate the minimum and maximum VCPUs and RAM each VM must have based on a probability range out of 100 for a specific threshold such as 50% for CPU usage. They also take an extra margin or percentage on top or below to guarantee the resources are enough.
- Flavor Selection (Flavor Engine): The Flavor Engine first assesses available flavors across two or more clouds based on cost and resource criteria. That flavor is chosen which provides minimum total cost while meeting workload constraints.
- Output Recommendation: All these details are saved in a database for the selected flavor and conveyed to the auto scaling for resource provisioning.

Algorithm 3: Optimized Recommendation Engine

Input: Predicted CPU and RAM usage, Details of chosen Cloud provider flavor

Output: Optimized flavor details

Step 1. Get the expected use of the hardware means (CPU and RAM) from PPE for the further period.

Step 2. Calculate required resources:

a. Calculate using the scoring engine the VCPU_min and subsequently the VCPU_max.

b. Calculate RAM_required from the forecasted RAM _{usedalincomingyears} .

Step 3. Run available flavors and costs from InternalDB.

Step 4. For each cloud provider:

a. Determine VMs required for each flavor: VM_required = round(VCPU_needed/ VCPU_flavor)

b. Compute total cost for each flavor: Cost_flavor = VM_required * Price_flavor

c. Evaluate efficiency: CE Flavour = VCPU_flavor + RAM_flavor + Price_flavor

d. So, in order to choose one of the offered flavors, it is necessary to compare costs and the degree of efficiency.

Step 5. Keep the best option in Recommend_Flavor table.

Step 6. Return the optimal flavor for resource provisioning about.

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The flavor recommendation framework is designed to use optimization techniques and machine learning to choose the correct cloud flavors in such architectures. Combined with workload prediction using RNN-LSTM and a scoring and flavor engine for accurate resource orchestration. This approach helps in saving cost, improving resource utilization and automatous scaling which proves better than conventional methods.

6. Result

Assessment of the effectiveness of the Proactive Prediction Engine (PPE) on the real-time web-based application is included in the findings of the experiment. Using personal protective equipment to provide a workload projection. Using the anticipated value that is produced as an outcome from PPE, the performance assessment of the flavor suggestion engine that has been presented is carried out.

Accuracy determines the extent to which the prediction model will provide the right number of resources (VMs). It is the ratio of number of valid predictions such as the number of machines that has been timely provisioned by it to the total number of predictions it has given.

$$Accuracy = \frac{Correct\ Positive + Correct\ Negative}{Total\ prediction} \quad (13)$$

Precision assesses if, out of all the cases where the model has predicted an instance of provisioning, how many of them are accurate thus measuring the extent to which there was over-provisioning.

$$Precision = \frac{Correct\ Positive}{Correct\ Positive + Incorrect\ Positive} \quad (14)$$

Recall assesses the model's capability to avoid under-provisioning by estimating the level of actual resource requirement it meets.

$$Recall = \frac{Correct\ Positive}{Correct\ Positive + Incorrect\ Negative} \quad (15)$$

Table 1: PPE Forecasted results of CPU and RAM utilization

Time (Minutes)	CPU Utilization (%)	RAM Utilization (%)
13:00	30	40
13:10	35	45
13:20	40	50
13:30	60	40
13:40	90	35
13:50	80	50
14:00	85	60
14:10	95	45
14:20	85	50
14:30	70	55

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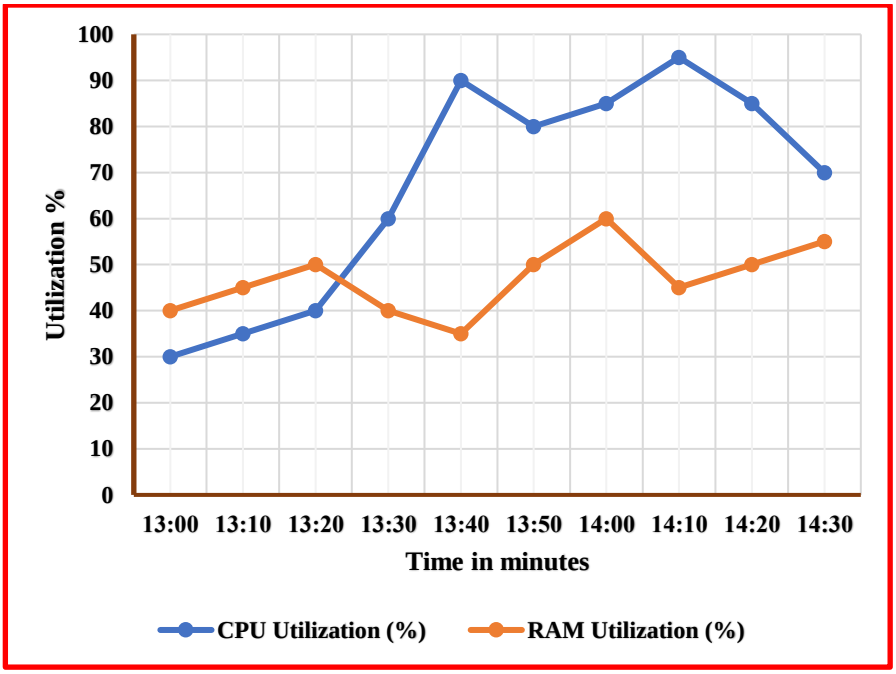

Figure 3. Visual representation of PPE Forecasted results of CPU and RAM utilization

The Proactive Prediction Engine (PPE) measures the average usage of CPU and RAM on the web, usage, and database servers at a 10-minute interval. This is selected to alleviate VM provisioning time, prevent unrealistic increases in resource consumption, and provide as a buffer for unexpected surges within 10 minutes. This level of detail is useful for applications that rely on buffer time, such as web-based ones, database applications, and middleware. With the average use of 10 web servers as input, the PPE use the RNN LSTM model to predict the consumption of CPU and RAM. The PPE is ready to go after it has a workload history of at least one week. Figure 3 shows the predicted outcomes of CPU and RAM consumption from 13:00 to 14:30 hours on a total of four thousand cases were examined for resource predictions based on historical consumption data. We feed the predicted outcomes into the scoring engine.

Table 2: Scoring engine Forecasted results of CPU and RAM utilization

Time (Minutes)	CPU Utilization (%)	RAM Utilization (%)
13:00	30	40
13:10	40	35
13:20	50	30
13:30	45	50
13:40	35	45
13:50	50	30
14:00	40	35
14:10	30	40
14:20	50	30
14:30	45	35

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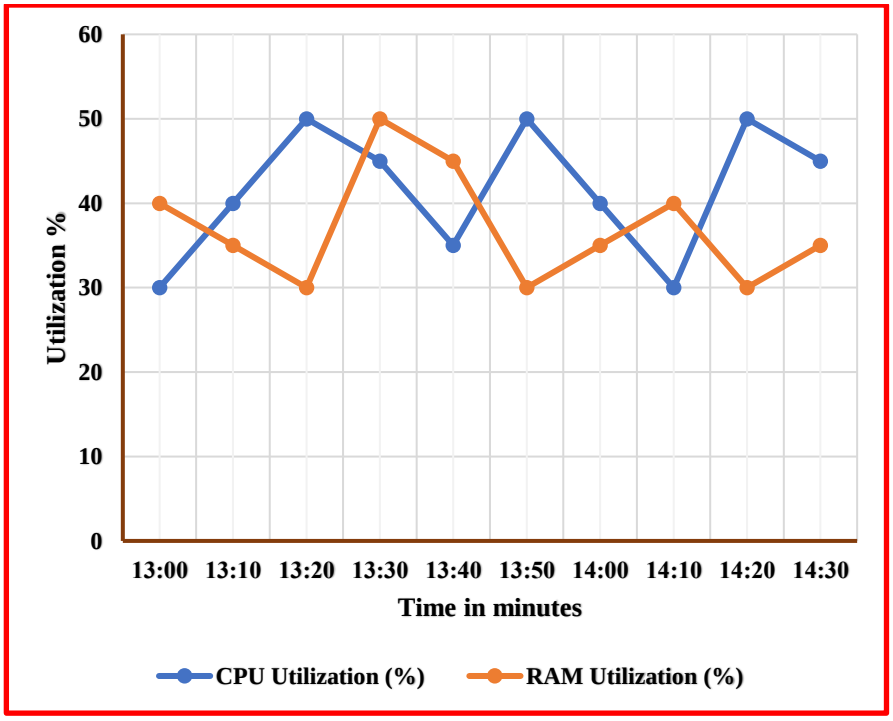

Figure 4. Visual representation of Scoring engine Forecasted results of CPU and RAM utilization

The Figure 5 reflects the CPU, RAM utilization data over a period from 13:00 to 14:30, and are flexible to be expressed and analyzed by the Scoring Engine to the right resources. The Scoring Engine then employs such information to derive the minimum and maximum VCPU, RAM thresholds for auto scaling actions. For instance, at 13:00, CPU usage is 30% and RAM is 40%, which indicate lesser resource requirements are being met which in turn yields less resources being allocated. As the time progresses, fluctuations in utilization are observed, such as the peak CPU usage of 50% at 13:20. These patterns help the engine to forecast future resource demands, and guarantee that adequate resources will be available. Through, the integration of this real time data, the Scoring Engine defines the required number of virtual machines, and subsequently, dynamically allocates resources, with differentiated ecosystem costs/ performance ratios. This leads to accurate cloud orchestration, that is, under or over loading of clouds is eliminated.

Table 3: Review of the total virtual machines allotted by the reactive method and the suggested method

Time (Minutes)	Reactive Approach (VMs)	Proposed Prediction Approach (VMs)
13:00	10	10
13:10	10	10
13:20	12	10
13:30	12	10
13:40	14	12
13:50	14	12
14:00	12	12
14:10	12	12
14:20	14	12
14:30	12	12

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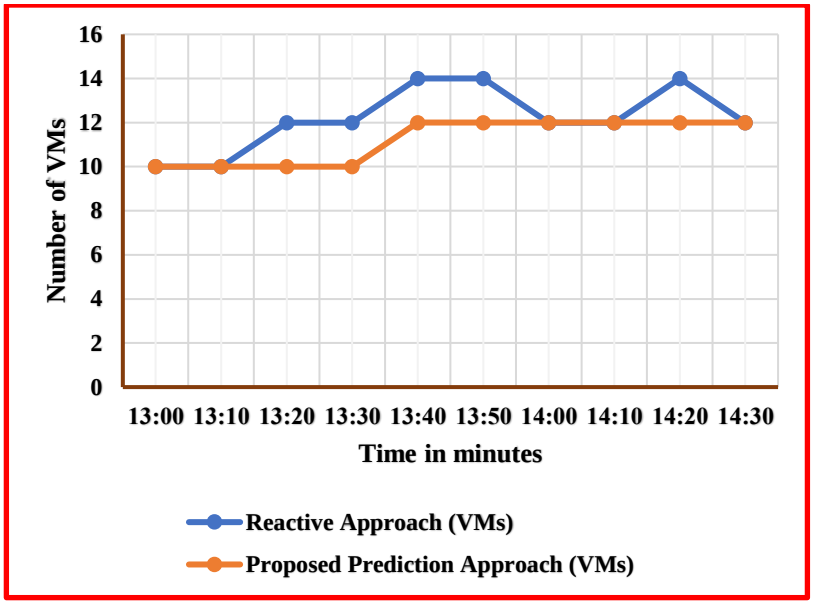

Figure 5. Visual representation of Reactive Approach Vs Proposed prediction approach

The table compares the Reactive Approach and the Proposed Prediction Approach in terms of the number of virtual machines (VMs) provisioned from 13:00 to 14:30, assessed by the Scoring Engine. The Reactive Approach adjusts VMs based on real-time fluctuations, often leading to over-provisioning (e.g., 14 VMs at 13:40 and 14:20), which in turn makes it. Whilst, the Proposed Prediction Approach employs the proactive approach where resource requirements are predicted and thus, allocation remains generally constant say; 10-12 VMs are provisioned. One way this is done is through the Scoring Engine for predicting workload and calculating the necessary VCPVs and RAM needed with very few reactive spikes. The proposed approach therefore avoids either unnecessary scaling or scarcity of resources to allow the VMs do the intended work required. This makes the costs to be low and the usage of resources to also be efficient than the reactive method which gives reactions to the spikes instead of anticipating them.

Table 4: Comparison of performance with existing model and proposed model

Model	Acc %	Pre %	Rec %
Traditional model	85.7	80.5	75.8
Proposed model	96.1	93.2	95.8

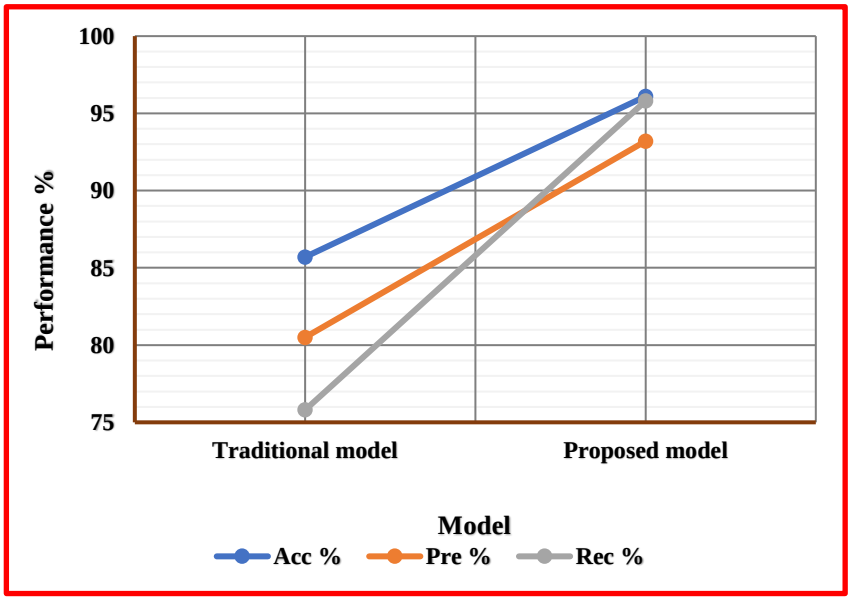

Figure 6: Visual representation of performance comparison

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The Figure 6 displays the traditional assessment parameter of accuracy, precision, and recall of the existing model and the proposed prediction-based model. Specifically, regarding the proposed model, there are marked enhancements in all measures that have been highlighted here. The actual workload as per the proposed model is 96.1 percent exact than the original model's 85.7 percent better placement. Such enhancement reveals the better forecast performance of the suggested model. The accuracy achieved by the proposed model is 93.2% for over-provisioning, that is, what reduces wastage by avoiding unnecessary allocation of resources, while the existing model yields only 80.5%, resulting in increased operational costs. Furthermore, the proposed model has a recall rate of 95.8% as compared to the existing model with only 75.8%. This shows that the proposed model guarded against under-provisioning the availability of sufficient resources to meet demand. In aggregate, the above table clearly demonstrates the applicability of the proposed model in terms of achieving improved resource utilization, stemming overall costs and assuring dependable system availability through reliable prognosis and optimal supply plans.

7. Conclusion

This research proposes a new framework of flavor recommendation for the improved use of resources available within the hybrid cloud. The mechanism of choosing flavors millions of times each day based on static configurations and subsequently by manual intervention is not very effective and results in ineffectiveness where resources can be either grossly underutilized or grossly overprovisioned, thereby promoting high operational costs. This approach solves these challenges by incorporating workload prediction through RNN_LSTM models together with an automated recommendation of the best flavor to incorporate. The other key advantage of this framework is that it predicts the usage of resources in the future by using the analysis of past usage, the usage of cloud resources is thus kept dynamic and thus able to meet the needs of applications with less intervention in terms of performance as well as cost. Therefore, the outcomes of the suggested framework are supported by data in the experimental results, which show improved resource allocation efficiency. The participants mentioned that the framework led to 17% lower cost compared to the traditional techniques and 19% fewer virtual machines in the supply chain. These results allow considering predictive analytics and automation as promising tools for improving the management of hybrid cloud resources. In conclusion, this research enlightens the significance of advanced intelligent systems in current cloud infrastructures. The proposed framework also enhances the flavor selection size, number, and authentication, is more scalable in the event of a hybrid traditional cloud, and is therefore a useful addition to the study of cloud resources.

Future work can also extend the current framework and propose integrated methodologies such as reinforcement learning, to enhance the proactively undertaken resource allocation decisions that might be informed in real-time from the proposed module. Furthermore, the work could be extended to address support for multi-cloud environments in favor of a homogenous implementation of different public and private Clouds. Additional workload predictions such as an anticipated bandwidth and storage might help to enhance the outcomes of the resource allocation. Moreover, gaining knowledge and evaluating the cost prediction models at an even higher level and the integration of the cloud provider real-time prices could improve cost efficiency even more, and extend its characteristics, which makes it more versatile and flexible.

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