Cloud Cost Estimation Using a System Dynamics Approach

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Abstract

The rapid adoption of cloud computing has increased overall infrastructure, supply chain complexities, and cloud costs. Cloud costs may remain the same if appropriately managed, affecting operational efficiency and organization budgets. This search helps to understand the system dynamics model of cloud cost estimation that considers the interaction of various resource and cost variables with their influence on each other, including available cloud resources, resource consumption, and resource provisional. The model identifies potential impacts on cost estimation, resource utilization, and service quality through simulations. The proposed SD model allows decision-makers to analyze different "what-if" scenarios and evaluate different policies for cost estimation. This enables them to determine the most effective equilibrium strategy regarding cost and productivity. using Vensim© software, the assistant dynamics model is created. The team analyses the impact of different parameters on cloud cost.Vensim© provides simulated results like graphs to show specific scenarios that help estimate cloud cost and improve resources, highlighting the importance of estimation strategy. This study helps cloud service managers make data-driven precision decisions, ensure insurance cost-effectiveness, and make sustainable use of cloud resources.

Keywords

System dynamics, Cloud Cost Estimation

1. Introduction

Cloud computing has revolutionized business operations by providing robust and adaptable IT resources. However, maintaining various sources could be challenging because of shifting workloads and intricate price patterns.

Conventional cloud management techniques often rely on personal virtual computers, which can be ineffective and time-consuming. A more thorough approach is required to optimize the entire cloud environment. This study suggests employing System Dynamics to model and analyze the intricate relationships between various elements influencing cloud costs and productive resource usage. Cloud computing is an emerging technology that is growing rapidly, with a market evaluation of $160 B by 2020, after a moderate beginning of around $6B in 2008.

By understanding the relationships between various factors that influence each other, we can discover possibilities for cost reduction and find efficiencies in the system. We aim to estimate cloud costs and ensure cloud services meet performance standards. We will use a software program tool known as Vensim® PLE (Vensim is a registered trademark of Ventana Systems, Inc.) to create a detailed version that considers workload fluctuations as changes in call for an impact on resource utilization and costs. Resource provisioning can drastically impact costs. Different types of prices, such as hourly cost, reserved or spot instances, have different cost implications. Monitoring elements like available resources, number of uses, and number of requests for accessing cloud services per hour can assist in identifying estimation opportunities.

This research will help organizations make informed selections regarding cloud usage, leading to tremendous value savings and advanced career best.

The model has three broad cost estimation categories: resource consumption, resource provisioning, and cloud virtual machine (VM) cost of $0.096 per vCPU-Hour for Windows (Amazon E2C). For the model's simplicity, we only consider the CPU as a resource and avoid memory as a resource.

We consider CPU units vCPU (Virtual CPU) units rather than Megahertz (MHz) to estimate the resources. Also, considering workload intensity (Chhetri et al., 2023) due to increasing requests and efficiency factors due to the available resources for consumption virtually.

2. Literature Review

Cost Minimization of Service Deployment in a Public Cloud Environment

The authors have developed a new approach to deploying cloud services. Instead of setting up virtual machines, they focus on setting up tasks themselves. This means developers can specify how much work their service needs and the system will automatically determine where to put it. This is great for companies with complex infrastructure as it improves operational efficiency and saves costs. The best part is that this process is easy, even for people who are not experts in cloud computing. This allows various users to access cloud services (Legillon et al., 2013).

Resource Allocation for IAAS Cloud

This section discusses hosting servers online. Companies offer a variety of virtual servers, each with its costs and capabilities. It's like renting a different-sized apartment – you'll pay more for more significant, but you'll get more space and energy. The goal is to use these servers more efficiently to save money and meet customer needs. Therefore, companies need to figure out how best to offer these servers to different customers to reduce costs and ensure that everyone's needs are met. This requires careful planning and monitoring (Legillon et al., 2013).

In this regard, Mokhtari, Azizi, and Ghabli (2024) proposed a new paradigm for cloud resources. The speed and cost of cloud servers — a perennial central cloud computing problem that they zeroed in on. The solution is a smart prioritisation strategy that responds to events, allowing you to find the sweet spot between cost and performance. This method does not use fixed priorities, which are normally in traditional methods. It is more efficient, as it can dynamically adapt to changing needs.

The researchers compared their method with another popular one and found that it significantly reduced costs and improved efficiency. To validate their approach further, they propose testing it in real-world cloud systems. This will demonstrate the benefits for cloud service providers and users who want to improve their resources.

Profit Estimation Techniques for Cloud

Cong and others. (2020) explored ways for cloud service providers to maximize revenue in a competitive market. They looked at ways to increase revenue and reduce costs. The study proposed that firms should offer high-quality services in order to optimize both revenue and customer satisfaction. That way customers return instead of facing penalties. We also talked about intelligent pricing strategies such as demand-adjusted prices or auction systems in order to achieve optimal pricing for goods. The purpose of the study was to optimise virtual network functions by consuming less energy, thereby reducing costs through efficient resource management. Which means maximizing the usage of resources and cutting down on excess expenses.

In conclusion, the research shows that to thrive in the market, there has to be a proper equilibrium among pricing versus quality versus cost-effectiveness. This is key information for cloud providers to adapt to an ever-evolving industry.

Cloud Estimation in Cloud Provisioning

Researchers have developed an intelligent way to reduce the cost of cloud computing. Particle Swarm Optimization (PSO) helps to find the best combination of servers and determine their pricing (hourly or in advance). The methodology considers tasks to be performed, delivery time, and importance.Using PSO, it is possible to obtain the lowest cost schedule of these services on a beneficia server. The researchers discovered that modelling projects in a more flexible manner can deliver substantial savings. This method is effective for simple projects but the costs are greatly reduced due to complex projects. This research shows that applied swarm intelligence can be useful to make cloud computing economical by optimum allocation of resources (Netjinda et al., 2012).

Recent research by Mei Li (2023) focused on integrating financial management practices with cloud monitoring tools to save money on cloud services. Lee highlighted the importance of keeping a close eye on cloud costs, especially in terms of pricing and complex billing structures that various cloud providers have more concern.

Emphasis on tools such as IBM's Klarity, which can aid and manage an organization's cloud spend across multiple service providers. When budgeting practices are combined with real-time analytics, organizations can have better control of their cloud spend. When finance, IT and operations teams work together, it helps make data-driven decisions for resource utilization and effective alignment of cloud spending with business goals.

Cloud Market analysis

Cloud providers can attract and sustain customers in a competitive market. They offer competitive prices, excellent service, and exceptional products. Finding the right balance between cost savings and increased productivity is critical. In addition, providing services that meet the needs of specific customers can be very profitable.
Studies show that combining affordable pricing and superior service can help cloud providers gain more market share. This highlights the need for cloud providers to make careful planning and decisions to succeed in today's competitive landscape (Nazareth et al., 2021).

Think of the cloud service provider and its users as players in the game. The provider wants to make more money, while the users want the best service. This paper proposes a framework in which the provider sets rules (server allocation and pricing), and users adjust their requirements accordingly.
The researchers used a mathematical technique called the Stackelberg game to model this interaction. They found ways to improve the situation to benefit donors and users. The provider can get higher returns, and the users can get better service. This approach demonstrates the power of collaboration between providers and users. By working together formally, the best results can be achieved for everyone involved (Liu et al., 2017).

By understanding and analyzing research work, I have taken several important variables that have a relation and affect the overall cloud cost. Cloud cost is dependent on various factors such as the availability of resources (memory, vCPUs, and other resources), their consumption rate, and how much time the user uses the resources, based on the demand; provisioning cost also increases, workload intensity (Chhetri et al., 2023) and much more describes in the system dynamics model.

3. Methodology

3.1. System Dynamics (SD)

System dynamics (SD) is a well-established modeling and simulation method developed by Jay Wright Forrester in 1958 to support long-term decision-making in industrial management (Chaerul et al. 2008). This approach is especially useful for complex systems like cloud cost estimation, cloud resource optimization, etc. SD is useful in analyzing complexity, non-linearity, and feedback loops in physical and non-physical systems (Forrester 1994). Through SD simulation, "What-if" scenario analysis and testing are possible for various policies (Richardson and Otto 2008). Therefore, SD is used widely to find how system behaviors evolve over time based on the system's structure and decision rules (Wolstenholme 1990). The SD model's variables are stock, flows, and auxiliary variables. To develop an SD model for application, it is necessary to create a Casual Loop Diagram (CLD) and a Stock Flow Diagram (SFD).

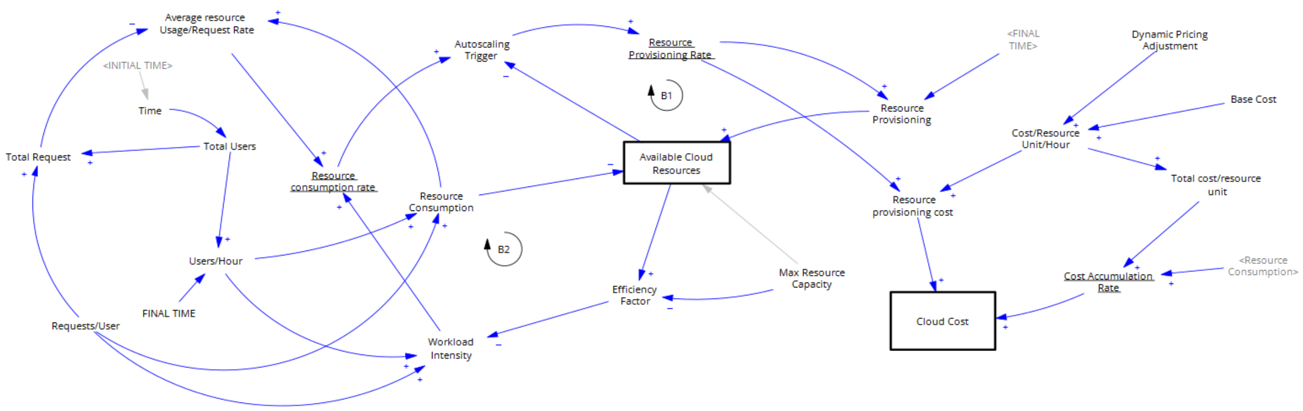
3.2. Casual Loop Diagram (CLD)
A Causal Loop Diagram (CLD) is a key tool for illustrating the feedback structure within a system (Chaerul et al., 2008). It represents how different variables interact and influence the system's dynamics with the help of visuals (Yuan, 2011). In a CLD. Arrows, known as causal links, connect various elements, showing their relationship. Each link has a polarity associated with it {positive (+) or negative (-)} that indicates the nature of the relationship. A positive sign indicates that the connected variable varies together with the changing of influencing variable, while a negative sign indicates contrary (Yao et al. 2018).

3.2. Cloud Estimation Model
The model is inspired by an earlier system dynamics model that examined the cloud capacity based on the cloud income (Nazareth et al., 2021). The model tells the estimated cost of a cloud server for using vCPUs as virtual resources over a network. The effect on cloud cost is tied to various factors that influence the cost, one factors are Available Cloud Resources (ACR), which tells how many resources are available for fulfilling the requests of the users; this variable is dependent on resource consumption negatively and resource provisioning positively. Resource consumption tells us how many resources i.e. vCPUs, are currently in use, which effects the ACR (-) negatively, Resource consumption depends on requests/Users and User/hour, which are a constant increasing variables that depend on total active users in the system which is increasing with the rate of 5% every hour and resource provisioning which informs us about the number of resources which are further added to the system to fulfill the increasing demand of resources, this variable is dependent on the resource provisioning rate and final time, resource provisioning rate tells the rate at which the system will allocate more resources it is based on the Autoscaling Trigger(AT) variable which is simply the ratio of Resource Consumption Rate to ACR. When this ratio is greater than 0.8, it means that out of available resources, 80% of the resources are consumed, indirectly affecting the workload on the system and reducing the efficiency of the system allocation process. To avoid this, we provision more resources to our system so that it works effectively and can fulfill the demand for upcoming resources without losing the system's efficiency.

Next, we have a variable named efficiency factor, which tells about how efficient our system is in delivering the number of resources to the user concerning the maximum resource capacity. This factor directly influences the workload intensity (Chhetri et al., 2023) of the system. Now, how do we know the workload intensity of the system? As the name says, workload means how much work is done by how many resources, or in other words, we can say how many requests are being generated by how many users. The workload intensity may also depend on various other factors, which are more complex based on the infrastructure of the system, but to seek simplicity for my model, I consider this way to calculate it quickly, but the relationship between other variables does not change. The workload factor then affects the system's resource consumption rate, which, as we know, further affects the autoscaling trigger.
This is all about the resource management part of the system. Now we discuss different cloud cost variables and their relationship to each other. To define the cost of the resource usage per

hour, I visited the Amazon E2C website (Amazon E2C) for getting some estimates about the cost of virtual CPUs. Then we discovered some dynamic prices on the website, and for the sake of understanding the relationship between the system variables, we took a cloud virtual machine (VM) cost of $0.096 per vCPU-Hour as a base cost for Windows. Since it is an estimated cost and can vary with respect to time, so we add an additional variable named Dynamic Pricing Adjustment which increase the price with 0.2% of growth rate. Cloud cost is estimated by total of resource provisioning and cost per resource unit. Resource provisioning cost is estimated by resource provisioning rate and cost of resource unit per hour. And cost accumulation rate is estimated by total cost per unit and total resources that are being consumed. The initial cloud cost value is taken to be approximately $357 (S. Chaisiri et al., 2010). We then study the estimated price in the future hours as per the increasing demand and number of users. Following is the structure of system dynamics model of cloud cost estimation:

Figure 1. Structure of the system dynamic model



As you can see, the model is having many variables and connection between them. The arrows represent the causal flow and the sign on the arrowhead i.e. (+, -) represent the impact of the variable in positively or negatively based on the relation with the respective variable.

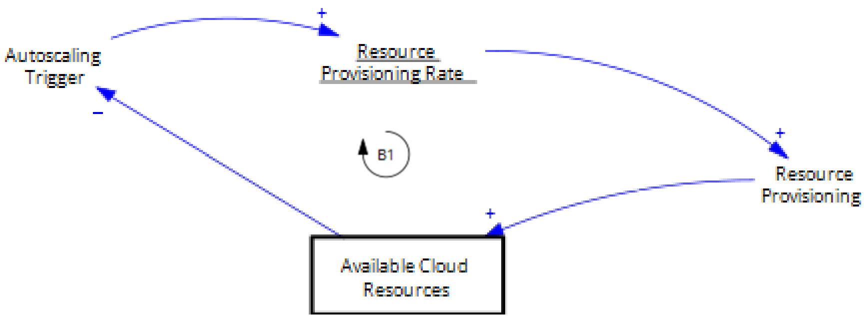
3.3. Causal loops

Causal loop diagrams are like paths for a complex system. They show how the different parts of the system are related and affect each other. Assume it as a diagram made up of arrow boxes, where the boxes represent the important elements of the system and how the arrows influence each other. These diagrams help us understand how the changes are related through the system, giving us feedback that amplifies or balances things (Tip et al., 2011).

In this model, there are 2 loops:

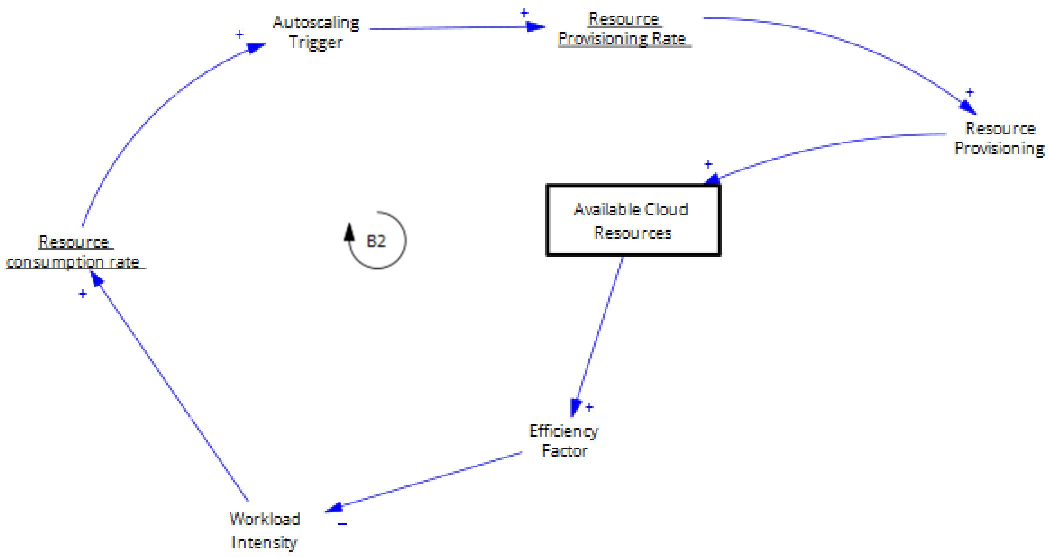
Loop 1: Available Cloud Resources -> Autoscaling Trigger -> Resource Provisioning Rate -> Resource Provisioning -> Available Cloud Resources

Figure 2. Causal loop 1



Loop 2: Available Cloud Resources -> Efficiency Factor -> Workload Intensity -> Resource consumption rate -> Autoscaling Trigger -> Resource Provisioning Rate -> Resource Provisioning -> Available Cloud Resources.

Figure 3. Causal loop 1



Loops 1 and 2 are balancing loops, a causal feedback loop that aims to stabilize the system by reaching a target or equilibrium state by countering changes or driving variables. It represents a feedback process where any deviation from the desired outcome reduces the disruption by triggering actions of the work. Balancing loops is critical for maintaining system stability, ensuring variables do not behave uncontrolled.

Since there is only one negative relation in both loops, i.e., ACR -> autoscaling trigger and Efficiency Factor -> Workload Intensity, these feedback loops are balancing loops. Due to this, we can see from the graph that, after some time, it reaches the equilibrium.

The system has 16 auxiliary variables, 2 stock variables (ACR, Cloud Cost), and 4 constant variables. Following is the list of variables names, equations and units:

Table 1. Dependent variables' equations and units

Variable Name	Equation	Units
Autoscaling Trigger	IF THEN ELSE (((Resource consumption rate / Available Cloud Resources)>0.8), 1, 0)	Dmnl [0,1]
Available Cloud Resources	INTEG (INTEGER (Resource Provisioning - Resource Consumption), Max Resource Capacity)	vCPUs
"Average resource Usage/Request Rate"	Resource Consumption / Total Request	vCPUs/requests
Cloud Cost	INTEG (Cost Accumulation Rate + Resource provisioning cost, 357)	USD
Cost Accumulation Rate	INTEG (Resource Consumption * 'Total cost/resource unit' / 100, 0)	USD/Hour
"Cost/Resource Unit/Hour"	Base Cost + Dynamic Pricing Adjustment	USD/vCPUs
Dynamic Pricing Adjustment	INTEG (0.002, 0.002)	USD/vCPUs
Efficiency Factor	Available Cloud Resources / Max Resource Capacity	Dmnl
Resource Consumption	INTEGER ('Requests/User' * 'Users/Hour')	vCPUs
Resource consumption rate	INTEG (INTEGER (Workload Intensity * 'Average resource Usage/Request'), 0)	vCPUs/Hour
Resource Provisioning	Resource Provisioning Rate * FINAL TIME	vCPUs
Resource provisioning cost	Resource Provisioning Rate * 'Cost/Resource Unit/Hour'	USD
Resource Provisioning Rate	INTEG (0.2*Autoscaling Trigger, 0.2)	vCPUs/Hour
"Total cost/resource unit"	'Cost/Resource Unit/Hour' / 100	USD/vCPUs
Total Request	'Requests/User' * Total Users	requests
Total Users	INTEGER (50 + 2*Time+10*SIN(0.5*Time))	User
"Users/Hour"	INTEG (Total Users / FINAL TIME, 10)	User/Hour
Workload Intensity	'Users/Hour' * 'Requests/User' - Efficiency Factor	requests/Hour

Table 2. Quantitative variable values

Variable Name	Value	Units
Base Cost	$ 0.092	USD/vCPUs
FINAL TIME	100	Hour
Max Resource Capacity	28,000	vCPUs
"Requests/User"	5	requests/User

4. Results and discussion

The System Dynamics model developed in this research gives significant insights into the behavior of cloud cost with various demand conditions and resource allocation strategies. Through the simulation conducted using Vensim®, several observations that are concluded are:

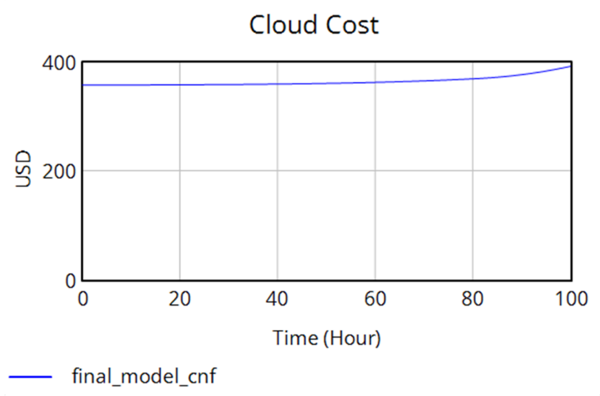


Figure 4: Cloud Cost

4.1. Impact of Autoscaling on Cloud Costs: A scenario highlights how the autoscaling trigger mechanism, activated when consumption reaches 80% of available resources, plays an important role in controlling costs by automatically providing additional resources to meet demand it does not emphasize system performance and performance degradation. This leads to a constant increase in resources but a controlled increase in costs, which means that just-in-time delivery is critical to balance efficiency and the costs involved.

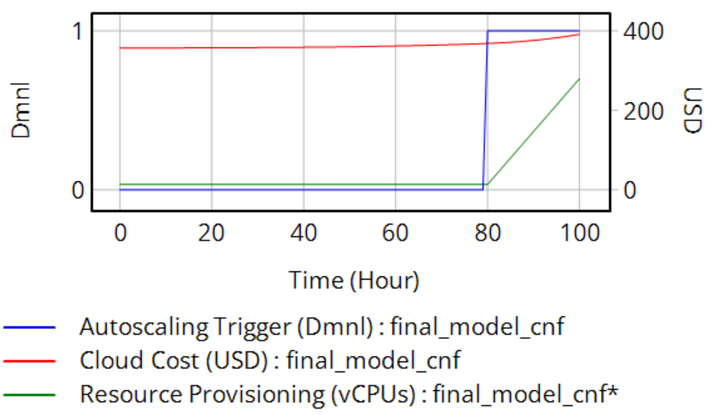


Figure 5: AT,Cloud Cost and Resource Provisioning

As the graph shows, when the autoscaling triggers changes from 0 to 1, resource provisioning increases as more than 80% of resources are utilized, and cloud cost increases simultaneously.

4.2. Resource Utilization Efficiency: High simulation results lead to lower cloud costs due to the inference that higher resource utilization induces good operational efficiency as it helps to minimize waste, resulting in low operational spending and, hence, improving aggregate efficiency. This emphasizes the requirement for system efficiency techniques such as workflow scheduling and load balancing.

4.3. Incorporation of Dynamic Prices: The model includes dynamic price changes to reflect changing regional costs. Smaller price increases (0.2% growth rate) can have a larger effect on total cloud costs. Clearly, strategies that illustrated cost-saving measures – reserving samples or greater resource efficiency activating massive cost reductions showed the power of pricing strategy, including scenarios that articulate changes that will control costs**.**

4.4. Various what-if: "What if" theories have outlined how policies can affect cost savings and resource utilization. For example, compared to reactive resource allocation, advanced resource planning based on forecasted demand resulted in better preparedness and cost savings. Still, oversupply and failure to adequately forecast demand resulted in waste and increased costs. The ability to analyze these scenarios gives cloud service managers a powerful decision-making tool.

4.5. Balance Loop Effect: The two balance loops identified in the model improved the system's stability by controlling material allocation and autocalibration triggers. Loops observed that as resource consumption increased, the system responded appropriately to the supply balance so as not to increase costs The results from the simulations showed that the system reached equilibrium over time, demonstrating the efficiency of equilibrium loops in maintaining cost and performance stability

4.6. Model simulation results

Let us study the relationship between the variables through simulation. As vensim® provides graphs, we can see the relationships of different variables.

4.6.1. Efficiency Factor and Workload Intensity:

In the graph, you can see that when autoscaling just triggers changes from 0 to 1, resource provisioning is first increased as more than 80% of resources are used and Cloud cost is gradually Increasing.

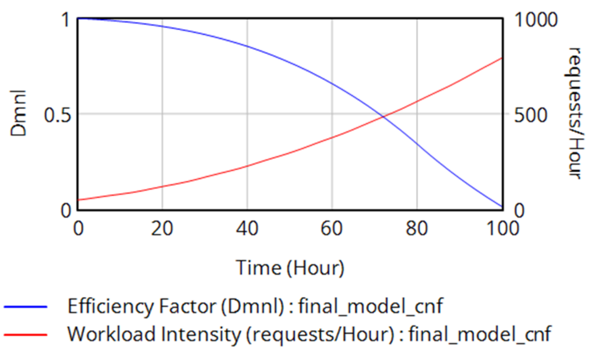


Figure 6: Efficiency Factor and Workload Intensity

4.6.2. Resource Consumption and Total Users: Here, as you can see in the graph, the total users vary with time. As we know, the number of users is not constant. It can vary with time, so to show the time-variant users, we have estimated an increasing sine curve formula that helps to take varying numbers of users and increases with time. The formula is 50 + 2*Time+10*SIN(0.5*Time). Here, time is an existing variable, increasing from 0 to 100 in hours as defined in the system. Now, we can see that as the number of users increases, resource consumption also increases. This is justifiable as more users mean more demand, which means more resource consumption.

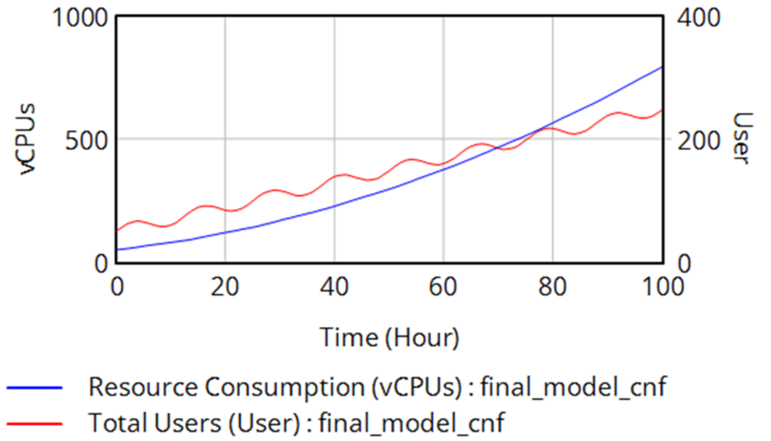


Figure 7: Resource Consumption and Total Users

4.6.3 Average resource per request, Resource consumption rate, and workload intensity: As the average resource usage and resource consumption rate increase, the workload intensity also increases. This is because workload intensity depends on available cloud resources and maximum cloud resources when the resource usage increases the workload intensity increases.

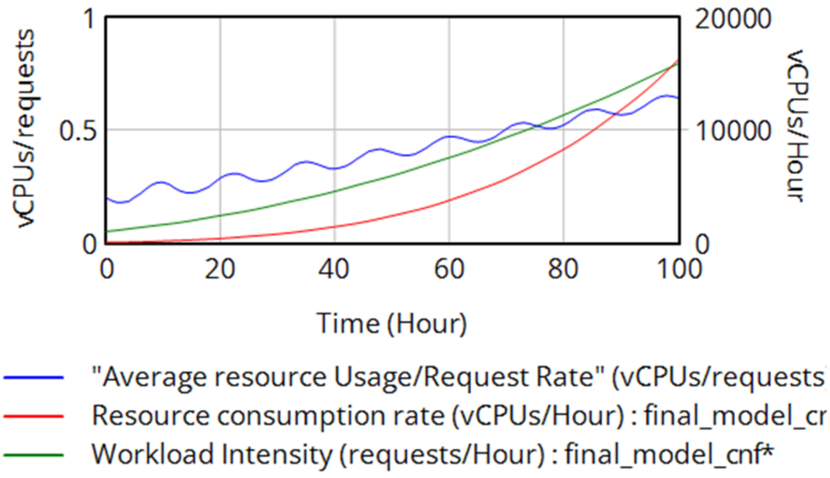


Figure 8: Average resource usage/ request, RCR and Workload Intensity

4.6.4. Cloud Resources Available and Resource Consumption Rate: From the graph, we note that as cloud resources available change from low to high, resource consumption rate changes from high to low. This is because they are in inverse relation with each other as the resource consumption rate lead the to creation of n number of available resources on system.

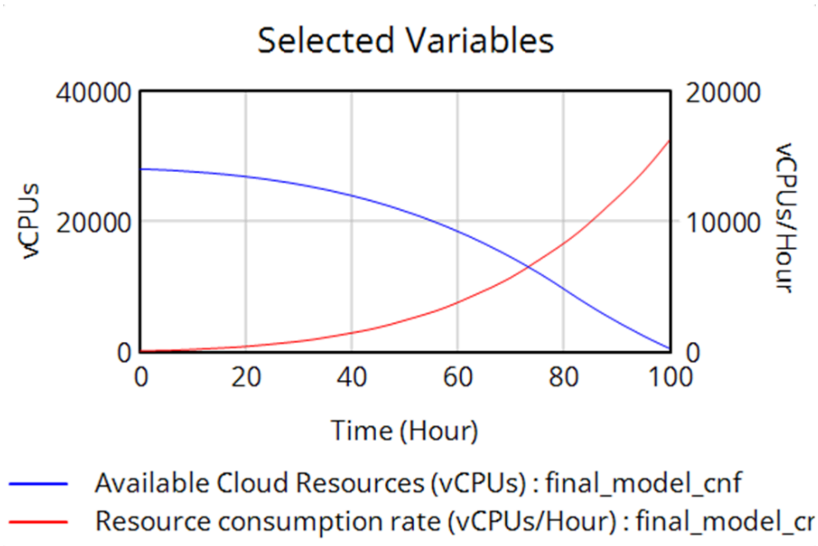


Figure 9: ACR and RCR

4.2. Model Validation

To ensure the accuracy and reliability of cloud cost estimates, a system dynamics model was developed, which required confirming the internal validity of that model. The model was first validated with theoretical expectations and earlier research in cloud cost optimization. This included parameter examination where several fundamental aspects such as resource consumption, workload intensity, and cloud cost were compared between models based on existing relations known in the literature.
Next, they validated it where historical data was available. For example, the costs of cloud resources, user demand patterns, and autoscaling triggers defaulted to industry standard values using Amazon's vCPU pricing. This allowed us to simulate the model under these real-to-world conditions, thus enabling us to observe how well it mimics the trend exhibited by actual cloud costs due to resource demand variations.

We also performed sensitivity analysis to ascertain how much parameters could be changed before the models failed to perform robustly. We modified parameters like autoscaling trigger thresholds, provisioning of resources, etc. to evaluate the response behaviour of the model and ensure constant behaviour despite varied conditions. This analysis helped to verify that the model is not overly sensitive to small parameter changes, showing robustness when modeling realistic examples of real clouds costs.

Lastly, the impacts of feedback mechanisms shown by causal loops are checked to ensure the balancing effects work adequately and maintain the system equilibrium as it is theoretically expected. In high resource demand scenarios, the model reached a state of equilibrium after several iterations, demonstrating its ability to model cost and resource stability over time. These validation steps imply that, as a representation of cloud cost dynamics, the model is trustworthy when used for scenario testing and policy analysis in the cloud cost management space.

5. Conclusion

This study demonstrates the effectiveness of using system dynamics modeling to analyze and optimize cloud cost estimates and resources. The model visualizes the complex interactions among important costs such as dynamic pricing, infrastructure, supply chain etc; an insight from this research is that when practical resources and self-quality of service assessment techniques are used strategic resources and cost reduction can scale much larger than expected The complexity cloud infrastructure captures. The capacity to map strategies also gives cloud admins a better talent of making data-centric decisions, which translate into cost efficiencies and business advantages The report further mentions that Dynamic price structure pitched with real-time and confirmation adjustments can drive costs down considerably at the same time dramatically increasing system efficiency. It further demonstrates the advantage of strength in self-monitoring systems to discover balanced information and counterbalance, avoid cost overruns, and sustainably and cost-effectively provide demand supply. Strategies can be designed to match business and budgetary requirements.

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