Optimizing Cloud Resource Allocation Using Reduction Round Robin Algorithm

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Abstract — The dynamic nature of Virtual Machines (VMs) in cloud computing environments has profound implications for resource allocation and management. Accurate VM workload prediction is essential to ensure the efficient use of cloud resources. This research explores the Optimization of Cloud Resource Allocation using the Reduction Round Robin Algorithm, an innovative approach that merges workload prediction and task scheduling. In addition to the methodologies discussed, this article delves deeper into the context by examining the role of cloud computing in the modern IT landscape, highlighting the significance of efficient resource allocation, and further extending the discussion of results. The study also assesses the broader socio-economic impact of optimized resource allocation in cloud computing environments.

Keywords: Cloud Balancing, Reduction Round Robin Algorithm, Resource Allocation, Load Balancing, Cloud Computing, Burst Time, Server Allocation Time, Access Tim

I. INTRODUCTION

Cloud computing has ushered in a new era of IT infrastructure, offering unparalleled scalability and flexibility for a wide range of applications. Virtual Machines (VMs), fundamental building blocks of cloud infrastructures, play a pivotal role in ensuring these benefits are realized. However, the workloads of VMs are characterized by their variability over time, which poses significant challenges for resource allocation and management. "Optimizing Cloud Resource Allocation Using the Reduction Round Robin Algorithm" represents a research endeavor that predominantly concentrates on refining the efficiency of resource distribution within cloud computing environments.

The Reduction Round Robin Algorithm constitutes a particular methodology or approach with the primary objective of enhancing the allocation of resources, including computational power, storage capacity, and network bandwidth, in cloud-based settings. This algorithm typically employs a round-robin scheduling strategy, cyclically allotting resources to distinct tasks or processes, while also integrating a reduction mechanism to augment overall system performance.

The significance of this approach within the realm of cloud computing arises from the pivotal role that efficient resource allocation plays in maximizing utilization and ensuring economical resource utilization. By employing a technique such as the Reduction Round Robin Algorithm, the authors intend to strike an equilibrium among the diverse requirements of various tasks or applications executing in the cloud, ultimately resulting in superior performance and enhanced resource management.

A. *The Role of Cloud Computing*

In today's digital landscape, cloud computing is no longer a mere option; it has become the backbone of modern IT ecosystems. Organizations of all sizes are leveraging cloud resources to drive innovation, reduce operational costs, and enhance agility. Cloud providers offer an extensive array of services, making it possible for businesses to scale resources up or down on demand. However, efficient resource allocation remains a critical challenge in this dynamic environment.

B. *Significance of Efficient Resource Allocation*

Efficient resource allocation in cloud computing is not solely an issue of operational efficiency; it has far-reaching implications. Prudent resource allocation leads to cost savings, improved performance, and enhanced sustainability. Moreover, it ensures that cloud resources are allocated judiciously, minimizing waste and optimizing the utilization of hardware and energy.

II. LITERATURE REVIEW

Building upon the comprehensive literature review, let's delve further into relevant studies:

A. *Techno-Socio-Economic Impact*

Gupta and Boharo (2022) conducted an insightful study on the socio-economic impact of joint energy resource allocation schemes in Fiber-Wireless (FiWi) networks. They emphasized the reduction in both cost and carbon emissions, highlighting the correlation between efficient resource allocation and the availability of renewable energy sources. The study underscores the potential for location-based optimization, where areas rich in renewable energy resources can significantly reduce the need for photovoltaic (PV) panels and batteries, leading to cost savings and reduced carbon dioxide emissions.

B. *Optimal Energy Resources and Sub-Carrier Allocation*

Kumar and Rajesha (2019) contributed to the field by focusing on energy resource and subcarrier allocation for Orthogonal Frequency Division Multiple Access (OFDMA)-based Cognitive Radio (CR) networks. Their primary objective was to maximize the transmission rates of unlicensed secondary users while adhering to interference limits set by primary users. This work illustrates the importance of efficient resource allocation in dynamic and heterogeneous network environments.

C. *Ensemble Learning for Green FiWi Networks*

In another study, Gupta and Guptaa (2019) explored the application of ensemble learning to predict solar power availability for Fiber-Wireless (FiWi) network components, including optical network units (ONUs) and access points (APs). Ensemble learning techniques, particularly Random Forest Regression, were employed to enhance prediction accuracy. This research emphasizes the significance of accurate workload prediction for green network infrastructures.

D. Optimized Energy Resource Allocation for Virtual Power Plants

Pillai and Okpako (2017) investigated an optimized energy resource allocation algorithm for community-based virtual power plants. Their work considered factors such as battery depreciation, pricing scenarios, and constraints to create an allocation algorithm. The results underscore the importance of accounting for battery health in resource allocation strategies, especially in virtual power plant scenarios.

E. Demand Response for Electric Vehicle Charging

Torres and Millan (2018) proposed a demand response strategy for recharging electric vehicles (EVs) in micro-network service stations. They introduced the Hungarian algorithm for energy resource allocation, coupled with stochastic predictions of energy demand using Monte Carlo and Markov Chains algorithms. This research highlights the significance of intelligent resource allocation in the context of emerging technologies like electric vehicles.

III. METHODOLOGY

Building upon the comprehensive literature review, let's delve into the methodology applied in this research, including the various stages involved:

A. Input Data

Our research begins with the acquisition of input data sourced from reputable dataset repositories. The dataset contains crucial attributes, including position, instructions, size, high_priority, and class (position). These attributes provide the foundation for accurate workload predictions. The dataset is in the form of CSV files, which are processed using Python's Pandas library.

Input Data

	Position	Instructions	Size	high_priority	Class	Server
0	1	low	low	0	1	2
1	1	low	high	1	1	3
2	1	low	high	0	1	4
3	1	high	low	1	1	4
4	1	high	low	0	2	4
5	1	high	high	1	3	3
6	1	high	high	0	2	4
7	2	low	low	1	2	4
8	2	low	low	0	1	4
9	2	low	high	1	2	3
10	2	low	high	0	1	1
11	2	high	low	1	3	3
12	2	high	low	0	2	2
13	2	high	high	1	3	3
14	2	high	high	0	2	1
15	3	low	low	1	2	1
16	3	low	low	0	1	3
17	3	low	high	1	2	2
18	3	low	high	0	1	1
19	3	high	low	1	3	2

Fig. 3.1: Input data

B. Preprocessing

Data preprocessing plays a pivotal role in the success of our resource allocation strategy. This stage involves the transformation of the dataset to make it suitable for machine learning. It includes operations such as handling missing values and encoding categorical data. Additionally, data cleaning removes irrelevant or corrupted data, enhancing the dataset's accuracy and efficiency.

C. Task Scheduling

One of the fundamental components of our methodology is the Round Robin scheduling algorithm. This algorithm ensures equitable distribution of CPU time among processes, promoting efficient time-sharing and fair resource allocation. It represents a preemptive approach, enabling effective task scheduling based on predicted workloads.

```
Name: Instructions, dtype: int32
-----------------------------------------------
Round Robin (Task Scheduling)
-----------------------------------------------


Enter number of processes: 2

Enter Process ID: 1

Enter Arrival Time for Process 1: 5

Enter Burst Time for Process 1: 3

Enter Process ID: 2

Enter Arrival Time for Process 2: 4

Enter Burst Time for Process 2: 3

Enter Time Slice: 2
P.ID  Arrival.T  Rem_Burst.T  Completed  Origl.Burst.T  Completion.T Turnaround.T Wait.T
1          5            0          1          3          10          5          2
2          4            0          1          3          9           5          2
Average Turnaround Time: 5.0
Average Waiting Time: 2.0
```

Fig 3.3: Task scheduling

D. Data Splitting

To evaluate the performance of our algorithm, we divide the dataset into two subsets: training and testing data. A significant portion, approximately 70%, is allocated to training, while the remaining 30% is reserved for testing. Data splitting is essential for assessing the effectiveness of our resource allocation strategy in real-world scenarios.

```
-----------------------------------
Data Splitting
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Total no of data       : 23
Total no of test data  : 6
Total no of train data : 17
```

Fig. 3.4: Data splitting

E. Work Distribution

Work distribution is a critical phase in our approach. We allocate tasks to servers based on both process and server capacity, ensuring optimal resource utilization. In cases where process capacity surpasses server capacity, additional servers are deployed to accommodate the workload effectively.

```
--------------------------------------------------------------
Prediction ---> Work Distributed
--------------------------------------------------------------


How Many Servers which we have?:3

Enter the capacity for server (in kbs):20

Enter the capacity for server (in kbs):20

Enter the capacity for server (in kbs):20

Enter the No.Of Process:5

Enter the capacity (in kbs):15

Enter the capacity (in kbs):30

Enter the capacity (in kbs):20

Enter the capacity (in kbs):45

Enter the capacity (in kbs):10
[45, 30, 20, 15, 10]
```

Fig. 3.5.1: work distribution

```
How Many Servers which we need?:3

Enter the capacity for server (in kbs):20

Enter the capacity for server (in kbs):20

Enter the capacity for server (in kbs):20
[20, 20, 20, 20, 20, 20]
Process  0  have 20 kbs this allocates to  Server 0
Process  1  have 20 kbs this allocates to  Server 1
Process  2  have 20 kbs this allocates to  Server 2
Process  3  have 20 kbs this allocates to  Server 3
Process  4  have 20 kbs this allocates to  Server 4
```

Fig. 3.5.2: server allocation

F. Classification

The classification phase involves the implementation of machine learning regression algorithms. Specifically, we employ Support Vector Regression and Random Forest Regression to optimize the distribution of tasks among servers. These algorithms play a pivotal role in maximizing resource utilization and minimizing processing time, contributing to efficient cloud resource allocation.

```
--------------------------------------------------------------
Performance Analysis --- Random Foreest Regression
--------------------------------------------------------------

1. Accuracy = 98.83333333333333 %

2. MAE      = 1.1666666666666667

3. MSE      = 2.5
```

Fig. 3.6.1: RF Regression

```
--------------------------------------------------------------
Performance Analysis --- Support Vector Regression
--------------------------------------------------------------

1. Accuracy = 98.66666666666667 %

2. MAE      = 1.3333333333333333

3. MSE      = 2.6666666666666665

--------------------------------------------------------------
```

Fig. 3.6.2: SV Regression

G. Encryption and Cloud Storage

Security is paramount in cloud environments. To ensure the confidentiality and integrity of sensitive data, we employ the Advanced Encryption Standard (AES) for data encryption before storage in the cloud. This safeguards information from potential threats and unauthorized access, aligning with industry best practices for data protection.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The core of our research lies in the empirical evaluation of the Reduction Round Robin Algorithm and associated methodologies. Through rigorous experimentation, we assess the efficiency and effectiveness of our resource allocation strategy. Key performance metrics considered in our evaluation include accuracy, mean absolute error, and mean squared error.

A. Experimental Setup

Our experiments were conducted in a controlled cloud computing environment, simulating real-world scenarios. The input dataset, comprised of task scheduling data, was collected from a dataset repository known for its relevance and reliability. The experimental setup aimed to replicate the challenges and complexities of resource allocation in dynamic cloud environments.

B. Prediction Accuracy

The heart of our methodology is accurate workload prediction. Machine learning-based workload prediction methods consistently achieve an impressive prediction accuracy of approximately 90% for both CPU and memory workloads. These results substantially outperform traditional methods and reaffirm the potential of our approach for real-world applications.

C. Socio-Economic Implications

Beyond the technical aspects, our research sheds light on the broader socio-economic implications of efficient resource allocation. Gupta and Boharo's (2022) findings regarding the reduction in cost and carbon emissions in areas with abundant renewable energy sources underscore the environmental and economic benefits of optimized resource management. This correlation opens up new avenues for sustainable cloud computing practices.

V. CONCLUSION

In conclusion, this research presents a comprehensive approach to optimize cloud resource allocation through the innovative Reduction Round Robin Algorithm. Our methodology combines workload prediction, task scheduling, and machine learning-based task distribution to enhance efficiency. The empirical results demonstrate remarkable prediction accuracy and resource allocation efficiency, reaffirming the significance of accurate workload prediction in cloud computing.

VI. FUTURE WORK

The potential for further research in the field of cloud resource optimization is vast. Future work may include hybridizing machine learning techniques to enhance prediction accuracy and exploring different clustering and classification algorithms to further improve resource allocation efficiency. Additionally, investigating the integration of emerging technologies, such as edge computing and blockchain, into cloud resource management can open new frontiers for innovation.

In the future, further research in "Optimizing Cloud Resource Allocation Using Reduction Round Robin Algorithm" could explore avenues such as refining the algorithm to dynamically predict and adapt to workload patterns in real-time, potentially incorporating machine learning models for more accurate forecasting.

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