International Journal of Computing Sciences Research (ISSN print: 2546-0552; ISSN online: 2546-115X)
Vol. 8, pp. 3157-3170
doi: 10.25147/ijcsr.2017.001.1.210
https://stepacademic.net

Short Paper*

Modified Simple Linear Regression in Load Balancing Using CloudSim

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Date received: May 7, 2024
Date received in revised form: June 26, 2024; July 1, 2024
Date accepted: July 1, 2024

Recommended citation:

Meing, L. W. C., Gayyed, A. B., & Tandingan Jr., D. R. (2024). Modified simple linear regression in load balancing using Cloudsim. *International Journal of Computing Sciences Research*, *8*, 3157-3170. https://doi.org/10.25147/ijcsr.2017.001.1.210

**Special Issue on International Research Conference on Computer Engineering and Technology Education (IRCCETE). Guest Associate Editors: Dr. Roben A. Juanatas (National University-Manila) and Dr. Nelson C. Rodelas (University of East).*

Abstract

Purpose – This study addresses load balancing algorithms facing challenges in predicting resource usage for load distribution by exploring the incorporation of Pythagorean means (arithmetic, geometric, and harmonic) into regression models to enhance prediction accuracy for CPU, RAM, and bandwidth utilization in cloud environments.

Method – Focusing on the Round Robin Scheduling Algorithm, this paper introduces modified simple linear regression (SLR) models that integrate these means. Integrating these in the computation of a trendline function, computing then comparing the residuals on a sample dataset generated in CloudSim, is performed. A K-means model was used for comparison as it too was used in other literature.

Results – The findings reveal that incorporating the harmonic mean into SLR significantly reduces the mean squared error (MSE) in predicting CPU and bandwidth usage, offering a more nuanced approach to load balancing.

Conclusion – These results highlight the potential of harmonic mean-based SLR in refining resource prediction algorithms, suggesting an avenue for future research in developing more adaptable and efficient load-balancing strategies in cloud computing.

Recommendations – The study can be further validated in environments outside of CloudSim and further improved by adding the complexity of other measures of central tendency or linear regression methods.

Research Implications – The study encourages further exploration into cloud infrastructure optimization, the development of ML- enhanced load-balancing algorithms, and the use of other statistical means in ML. This suggests a broader impact, indicating areas for future research for strategies in load balancing and resource prediction in cloud computing environments.

Practical Implications – The improved load balancing and usage prediction capabilities could benefit cloud service providers and end-users and lead to more reliable, scalable, and cost-effective solutions.

Keywords – round robin, load balancing, cloud computing, Pythagorean means, modified linear regression

INTRODUCTION

There are many opportunities in the research domain of cloud computing. This paper aims to bridge a significant gap by exploring the possibility of predicting system resources via historical data using modified linear regression techniques to improve existing load-balancing algorithms. Despite the critical role of load balancing in optimizing cloud resource utilization, the literature reveals a scarcity of research focused on the predictive capabilities of load balancers using such advanced statistical methods. This paper seeks to address this shortfall by demonstrating how modified linear regression techniques can enhance the precision of resource allocation predictions, thereby improving the efficacy of load-balancing mechanisms.

With a simple and generalized algorithm for the assignment of tasks and processes, a cloud computing environment would have an optimized use of its resources alongside the potential to save energy without violating service level agreements. However, the integration of predictive analytics into load-balancing algorithms remains underexplored, presenting a notable problem: the underutilization of advanced statistical methods for improving load distribution efficiency based on CPU, RAM, and Bandwidth usage predictions.

For this article, load balancing is defined as a process of distributing workloads and computing resources in a cloud environment to optimize resource use, maximize throughput, minimize response time, and avoid overload on any single resource (Alhilali & Montazerolghaem, 2023; Almakdi et al., 2023; Semong et al., 2020). The literature reveals significant advancements in intelligent load balancing in cloud computing.

The Round Robin Scheduling Algorithm, a process scheduling method in computing, assigns a fixed time quantum to each process in a rotating order, ensuring equitable CPU time distribution. This mechanism prevents the monopolization of CPU resources by a single process and guarantees each process a chance to execute within a reasonable time frame (Marcelino et al., 2020).

In mathematical concepts and their applications, the Pythagorean means (Arithmetic, Geometric, and Harmonic) play a crucial role. By applying these means within the framework of simple linear regression, the researchers hypothesize that a more nuanced and effective predictive model for load balancing can be developed. The Arithmetic Mean is the most used mean, calculated as the sum of all values divided by their count. The Geometric Mean, more suitable for sets of positive numbers, multiplies all values and takes the nth root. The Harmonic Mean, often used for rates and ratios, is the reciprocal of the average of the reciprocals. In practical applications, these means, along with simple linear regression, find diverse uses. Simple linear regression, a technique to model relationships between a dependent and an independent variable, is widely used in statistical analysis, environmental modeling, and health sciences.

This investigation is propelled by the limited application of predictive modeling in load balancing within cloud environments, highlighting the necessity for a study that not only explores these statistical techniques but also assesses their practicality and effectiveness in real-world scenarios. These studies demonstrate the versatility and essential nature of these mathematical tools in various research fields.

LITERATURE REVIEW

Load Balancing

Load balancing in Cloud Computing is a process that distributes workloads across multiple computing resources, such as servers or network links. This distribution is essential to ensure efficient operation, avoid overloading any single resource, and maintain high levels of service performance.

Round Robin Algorithm, a simple yet effective load-balancing method, plays a critical role in this context. It allocates tasks to various servers sequentially and equally, ensuring no single server becomes a bottleneck. This algorithm's implementation in cloud environments is evident in its adaptability and efficiency in handling cloud-specific challenges like varying load patterns and scalability requirements

The literature reveals advancements in intelligent load balancing in cloud computing. For instance, Alhilali et al. (2023), Rout et al. (2020) and Semong et al. (2020) discuss the integration of artificial intelligence and machine learning techniques in Software Defined Networking (SDN). These approaches help in managing the growing network traffic efficiently, addressing challenges in latency, speed, and resource utilization. Almakdi et al. (2023) present a model using machine learning for load balancing in 5G networks enabled by SDN, emphasizing the role of agglomerative clustering and Back Propagation Neural Networks in network management. The study of Alhilali et al. (2023) offered a comprehensive survey of AI-based load balancing techniques in SDN, highlighting the potential of AI in improving network resource usage and overall performance. Lastly, Varalakshmi et al. (2022) explored the application of algorithms like Round Robin and Least Connection in SDN, demonstrating improved throughput with Mininet simulations and POX controllers. The conclusions drawn from the articles on load balancing in cloud computing emphasize the crucial role of advanced technologies and algorithms. Thus, the integration of machine learning in SDN significantly enhances load balancing, addressing key challenges in network management. These articles collectively indicate a trend towards more intelligent approaches to load balancing, reflecting the evolving needs of complex network systems.

While these studies demonstrate the evolving nature of load-balancing techniques, incorporating AI and ML, several gaps and opportunities for further research emerge. For instance, the effectiveness of AI and ML in dynamic and highly scalable cloud environments requires deeper investigation, especially in terms of real-time data processing and the adaptability of algorithms to sudden changes in workload patterns. The integration of AI and ML in load balancing also raises questions about the complexity and computational overhead these techniques introduce, potentially affecting the overall efficiency and response times of cloud services.

Moreover, the analysis of traditional algorithms like Round Robin and Least Connection, as explored by Varalakshmi et al. (2022), with AI-enhanced methods, offers valuable insights into their respective strengths and limitations. However, it also highlights the need for a more nuanced understanding of how these methods can be effectively combined or adapted to meet the specific requirements of modern cloud infrastructures.

These discussions highlight a trend towards more intelligent, AI-driven approaches to load balancing, reflecting the evolving needs of complex network systems. The critical examination of current literature not only identifies the strengths of incorporating ML into load-balancing strategies but also opens new avenues for research. Specifically, it suggests the exploration of hybrid models that blend the simplicity and efficiency of traditional algorithms with the adaptive, predictive capabilities of AI and ML. Such models could potentially offer a balanced solution to the challenges of managing highly dynamic and scalable cloud environments.

Round Robin

The Round Robin Algorithm has been the subject of various enhancements aimed at addressing its inherent limitations and adapting it to the complexities of modern computing environments. A critical examination of the literature reveals a concerted effort to refine the algorithm's efficiency and applicability across different systems.

Iqbal et al. (2023) pioneered the incorporation of dynamic time quantum adjustments and priority considerations, marking a significant departure from static scheduling methods. This innovation not only improves task execution in real-time systems by adapting to the workload's nature but also underscores the necessity for flexibility in task scheduling algorithms.

Alhaidari and Balharith (2021), through their development of an enhanced round-robin algorithm for cloud computing, focused on optimizing task scheduling and resource management. Their work is pivotal in demonstrating how algorithmic adjustments can lead to more efficient resource utilization, a key concern in cloud environments where resource demand fluctuates unpredictably.

Mostafa and Amano’s (2020) proposal of a K-means clustering-based approach to reduce time costs introduces a novel perspective on integrating machine learning techniques with traditional scheduling algorithms. This combination promises not only to enhance efficiency but also to automate the optimization process based on historical data, pointing towards a more intelligent system design.

Marcelino et al. (2020) comparison of quantum time calculations (arithmetic, geometric, harmonic means) in dynamic round-robin scheduling reveals the harmonic mean as the most effective, highlighting the potential of statistical means to refine scheduling accuracy and efficiency. This finding directly aligns with the research focus on leveraging mathematical models to improve load-balancing strategies.

Balharith and Alhaidari (2019) and Alsulami et al.'s (2019) work further contribute to the discourse on quantum time selection, offering insights into the algorithm's adaptability and efficiency in CPU scheduling. Their comparative analyses of different round-robin variants, including Adaptive and Best Time Quantum, provide a roadmap for future enhancements in algorithm design.

Azzini et al.'s (2018) investigation into round-robin scheduling in web servers, with a focus on NAProxy and NGINX, broadens the algorithm's application scope. This exploration into web server load balancing underscores the versatility of Round Robin and its potential integration with emerging web technologies.

Patil and Aeloor (2017) reviewed different scheduling algorithms in cloud computing, including round-robin. Pradhan et al. (2016) modified the algorithm for better resource allocation in cloud computing. Akashdeep et al. (2014) and Ndiki et al. (2010) reviewed scheduling algorithms in IEEE 802.16 networks, focusing on Quality of Service. Li et al. (2005) proposed a Dynamic Weighted Round-Robin method for network load balancing.

Lastly, Kanhere et al. (2002) introduction of Elastic Round Robin for network packet scheduling introduces a concept of elasticity, vital for accommodating the dynamic nature of network traffic. Their approach to fair and efficient packet scheduling exemplifies the ongoing evolution of the Round Robin Algorithm to meet the challenges of next-generation networks.

The collective advancements in round-robin scheduling not only demonstrate the algorithm's flexibility but also its potential synergy with machine learning models. This body of work lays the groundwork for a hybrid solution that combines the simplicity and fairness of Round Robin with the predictive accuracy and adaptability of machine learning. Such a solution could significantly optimize system resource use, enhancing cloud computing services and potentially reducing energy consumption. The research aims to build on these findings by exploring how a generalized machine learning model, when integrated with an enhanced round-robin algorithm, can lead to improved load balancing in intelligent cloud computing environments.

Pythagorean Means

The Pythagorean means to serve as fundamental statistical tools, each with distinct characteristics and applications. Understanding these means provides a solid foundation for their application in various domains, including cloud computing and load balancing.

The choice of which means to apply in specific cloud computing scenarios depends on the nature of the data and the objectives of the load-balancing strategy. While the arithmetic mean offers a general overview, the geometric and harmonic means provide nuanced insights into growth patterns and rate-based optimizations, respectively. This research leverages these means within modified simple linear regression models to predict resource usage more accurately. By integrating these mathematical tools, the paper aims to develop a more sophisticated approach to load balancing that can adapt to the dynamic nature of cloud environments, ultimately enhancing performance and resource utilization.

Arithmetic Mean

The arithmetic mean, represented by equation 1:

$$\frac{1}{n}\sum_{i=1}^{n} a_i \qquad \textit{Equation 1}$$

where ai represents the numbers and n is the count, is the most straightforward and widely used measure of central tendency. In the context of cloud computing, the arithmetic mean can offer a simple yet effective way to estimate average resource usage, such as CPU or bandwidth, over a set period. This estimation is crucial for initial load-balancing decisions where a baseline of resource distribution is needed.

Geometric Mean

The geometric mean, calculated in equation 2:

$$\left(\prod_{i=1}^{n} a_i\right)^{\frac{1}{n}} \qquad \textit{Equation 2}$$

shines in scenarios involving proportional growth or rates of change, making it particularly relevant for analyzing performance metrics that span multiple orders of magnitude, such as the scaling of cloud resources. Its application in cloud computing could be in the optimization of resource allocation over time, especially when considering growth patterns or the compounding effects of resource utilization.

Harmonic Mean

The harmonic mean is best suited for data sets involving rates, such as the speed of services or transactions per second, represented with equation 3.

$$n\left(\sum_{i=1}^{n} \frac{1}{a_1}\right)^{-1} \qquad \textit{Equation 3}$$

In load balancing, the harmonic mean can provide insights into the optimal management of resources by considering the rate-based metrics of cloud services, ensuring that resources are allocated in a way that minimizes bottlenecks and maximizes efficiency.

Simple Linear Regression

Simple Linear Regression (SLR) is a cornerstone statistical technique for modeling the relationship between two quantitative variables: an independent variable (predictor) and a dependent variable (response). The essence of SLR is in fitting a regression line through the data points to minimize the sum of the squared differences (residuals) between the observed and predicted values. This is represented by equation 4,

$$y=\beta 0+\beta 1xy=\beta 0+\beta 1x \quad \textit{Equation 4}$$

where y is the dependent variable, x is the independent variable, β0 is the y-intercept, and β1 is the slope, which facilitates predicting y for a given x.

The practical applications of SLR span a wide array of fields, evidencing its versatility and fundamental role in statistical analysis and research. For instance, Hayter et al. (2006) focus on confidence bands in linear regression models, underscoring SLR's critical role in estimating the precision of predictions and guiding decision-making processes. This aspect of SLR is particularly relevant in cloud computing, where predictive models can help allocate resources more efficiently by estimating future demands based on historical data.

Piotrowski and Napiorkowski (2019) demonstrate SLR's application in environmental studies, particularly in improving stream temperature models. The ability of SLR to model complex natural phenomena based on observable data points towards its potential in modeling cloud computing environments, which are similarly complex and dynamic.

In the context of public health, SLR's use in analyzing epidemiological data offers a blueprint for employing statistical models to understand and predict patterns of resource use and system performance in cloud infrastructures (Khan et al., 2021). The parallels between disease transmission models and cloud resource utilization patterns highlight SLR's capacity for revealing underlying trends and dependencies.

The application of SLR in assessing water quality parameters and modeling relationships in fractured porous media further illustrates its adaptability and power in extracting meaningful insights from varied data sets (He et al., 2021; Akhtar et al., 2021). These studies exemplify how SLR can be utilized to tackle specific challenges in cloud computing, such as predicting system load or optimizing data flow through complex network infrastructures.

The integration of SLR into cloud computing and load-balancing research offers a promising avenue for developing more accurate and efficient predictive models. By adapting SLR to the specificities of cloud environments, such as variable resource demands and performance metrics, researchers can devise sophisticated algorithms that dynamically adjust to changing conditions.

This study seeks to extend the application of SLR in cloud computing by modifying traditional regression models to incorporate Pythagorean means, aiming to enhance the accuracy of resource usage predictions. This innovative approach reflects a broader trend toward utilizing statistical models not just for analysis but as foundational elements of intelligent, data-driven decision-making processes in cloud computing.

The exploration of SLR in this context is not merely academic; it represents a practical step toward realizing more responsive and efficient cloud services. By leveraging the predictive power of SLR, cloud computing can advance toward a future where resource allocation is both anticipatory and optimally calibrated to the fluctuating demands of users and applications.

METHODOLOGY

Dataset Setup

The experiment was initiated with a simulation setup in CloudSim, a leading simulator for cloud computing environments (Goyal et al., 2012). The configuration includes 10 homogeneous physical servers, each equipped with 1GB RAM, 1.8GHZ CPU, and 1Gbps network bandwidth, running Linux OS with 8086 architecture. Each physical machine hosts two virtual machines, mirroring a configuration used in a similar study (Umadevi & Chaturvedi, 2017). This decision to replicate a known experimental setup provides a baseline for comparison and validation of the findings. A total of 1,000 instances for each virtual machine were generated. The dataset was then divided into a training (70%) and testing (30%) set, a standard split in machine learning research.

Experimentation

The study explores the impact of using geometric and harmonic means in the computation of the slope and intercept in simple linear regression (SLR) models, compared to traditional arithmetic mean-based calculations. This modification aims to assess the efficacy of these means in predicting resource usage within cloud environments more accurately. The Mean Squared Error (MSE) serves as the primary metric for evaluating the models' accuracy, where lower MSE values signify better predictive performance.

Additionally, the inclusion of a K-means clustering model as a comparative measure draws on its established use in machine learning for classification and prediction tasks. By comparing the performance of K-means with modified SLR models, the researchers aim to highlight the specific advantages and limitations of each approach in the context of cloud resource prediction.

In summary, the study culminates in the application of the models to the generated dataset, resulting in 24 unique models reflecting the combinations of dependent variables, independent variables, and the type of mean used. The comprehensive analysis of these models' MSE provides a detailed overview of their predictive capabilities, offering valuable insights for optimizing load balancing in cloud computing environments.

RESULTS

The results of the experiment showed that given predictive capabilities for load balancers in a cloud computing environment where a round-robin scheduler is used, there are a few considerations and comparisons to take note of as seen in Table 1.

Table 1. Summary Mean Squared Error

	CPU	RAM	Bandwidth
CPU - K-means		510,888.06	506,802.32
CPU - Arithmetic		252,301.13	254,080.81
CPU - Geometric		8,100,119.41	461,132.79
CPU - Harmonic		254,756.32	250,244.01
RAM - K-means	490,307.53		158,032.22
RAM - Arithmetic	444,148.06		84,050.80
RAM - Geometric	650,544.75		254,190.99
RAM - Harmonic	442,985.29		84,042.90
Bandwidth - K-means	486,849.77	158,052.81	
Bandwidth - Arithmetic	442,101.95	83,041.39	
Bandwidth - Geometric	1,139,550.50	171,667.74	
Bandwidth - Harmonic	440,875.21	83,045.96	

Models employing simple linear regression (SLR) with arithmetic and harmonic means demonstrated superior performance over the K-means-based approach, as evidenced by lower Mean Squared Error (MSE) values. The geometric mean SLR model exhibited an exceptionally high MSE, indicating a less effective fit for CPU usage prediction.

The arithmetic mean SLR model yielded the lowest MSE, suggesting it provides the most accurate prediction for RAM usage. In contrast, the K-means model, despite its utility in identifying data clusters, resulted in higher MSE values.

Both the arithmetic and harmonic mean SLR models showed low MSE values for Bandwidth usage prediction. The geometric mean SLR model, however, performed poorly.

DISCUSSION

The experimental results underscore the critical impact of selecting an appropriate mean for computing the regression models' slope and intercept, as well as the importance of the chosen dependent variable on the models' predictive performance.

The study's findings highlight the requirements of effective load balancing. This differentiation supports the notion that the choice of statistical mean and dependent variable directly influences the efficiency of resource allocation algorithms.

The results align with Marcelino et al.'s observations on the effectiveness of harmonic mean-based models in capturing network traffic trends. Furthermore, the confirmation of Kanhere et al.'s claim that optimizing resource use through informed model selection can enhance cloud computing services underscores the practical value of the findings.

The discussion extends beyond the mere implications of the findings to tackle the gap identified in the literature - the need for predictive models that can dynamically adapt to the varying conditions of cloud computing environments. By demonstrating the differential effectiveness of SLR models modified with Pythagorean means, the study contributes to a more refined understanding of how different statistical methods can be leveraged to improve load-balancing strategies. This insight is crucial for developing intelligent algorithms capable of optimizing resource use while minimizing energy consumption and enhancing service delivery.

CONCLUSIONS AND RECOMMENDATIONS

The harmonic mean SLR model shows promise, particularly for Bandwidth where rate-based predictions are relevant. The geometric mean SLR model's performance suggests a mismatch between the model's assumptions and the actual behavior of cloud computing resources, requiring further investigation or alternative approaches.

The analysis of the MSE from the predictive models demonstrates that the Harmonic Mean model exhibits a notable level of effectiveness across various resource usage predictions in a cloud computing environment. Overall, while the Harmonic Mean SLR model does not always surpass the Arithmetic Mean SLR model in performance, it shows its strength in specific contexts, particularly in CPU and Bandwidth usage prediction where it offers a more effective approach. The specific improvements in MSE, while sometimes marginal, are consistent enough to suggest that incorporating the Harmonic Mean into SLR could be advantageous for achieving a lower prediction error in certain resource usage scenarios. As such, the use of the model in live environments may be subject to future research alongside the adaptation to other linear models like multiple linear or polynomial regression.

IMPLICATIONS

The consistent performance of the harmonic mean SLR model across various resource types (CPU, RAM, and Bandwidth) highlights its robustness and reliability in predictive modeling within cloud computing environments. This model's ability to capture the central tendency of data without being unduly influenced by outliers or skewed distribution makes it particularly valuable for predicting average resource usage. Its effectiveness suggests that employing the arithmetic mean in SLR models can significantly contribute to minimizing prediction error, thereby optimizing resource allocation and enhancing overall system performance. Future research could explore the integration of these models with other machine learning techniques or the development of hybrid models that combine the strengths of arithmetic, geometric, and harmonic means to further reduce prediction error and enhance load balancing efficacy.

ACKNOWLEDGEMENT

Special thanks are extended to their faculty advisor Dionisio Tandingan, whose expert guidance, invaluable insights, and unwavering encouragement have been pivotal throughout the research process. Their contributions went beyond academic supervision, fostering an environment of intellectual growth and discovery.

FUNDING

The researchers express their deepest gratitude to the University of the Cordilleras for their generous financial support, which was instrumental in the realization of this research project. This funding enabled the presentation and publication of this document.

DECLARATIONS

Conflict of Interest

The researcher declares no conflict of interest in this study.

Informed Consent

Not applicable.

Ethics Approval

Not applicable.

REFERENCES

Akhtar, N., Ishak, M. Z., Ahmad, M. I., Umar, K., Yusuff, M. S. M., Anees, M. T., Qadir, A., & Almanasir, Y. K. A. (2021). Modification of the Water Quality Index (WQI) process for simple calculation using the Multi-Criteria Decision-Making (MCDM) method: A review. *Water*, *13*(7), 905. https://doi.org/10.3390/w13070905

Alhaidari, F., & Balharith, T. (2021). Enhanced Round-Robin algorithm in the cloud computing environment for optimal task scheduling. *Computers (Basel)*, *10*(5), 63. https://doi.org/10.3390/computers10050063

Alhilali, A. H., & Montazerolghaem, A. (2023). Artificial intelligence based load balancing in SDN: A comprehensive survey. *Internet of Things (Amsterdam. Online)*, *22*, 100814. https://doi.org/10.1016/j.iot.2023.100814

Almakdi, S., Aqdus, A., Amin, R., & Alshehri, M. S. (2023). An Intelligent Load Balancing Technique for Software Defined Networking based 5G using Machine Learning models. *IEEE Access*, *11*, 105082–105104. https://doi.org/10.1109/access.2023.3317513

Alsulami, A. A., Al-Haija, Q. A., Thanoon, M. I., & Mao, Q. (2019). Performance Evaluation of Dynamic Round Robin Algorithms for CPU Scheduling. *2019 SoutheastCon*. https://doi.org/10.1109/southeastcon42311.2019.9020439

Balharith, T., & Alhaidari, F. (2019). Round Robin Scheduling Algorithm in CPU and Cloud Computing: A review. *2019 2nd International Conference on Computer Applications & Information Security (ICCAIS)*. https://doi.org/10.1109/cais.2019.8769534

Goyal, T., Singh, A., & Agrawal, A. (2012). Cloudsim: simulator for cloud computing infrastructure and modeling. *Procedia Engineering*, *38*, 3566–3572. https://doi.org/10.1016/j.proeng.2012.06.412

Hayter, A. J., Wynn, H. P., & Liu, W. (2006). Slope modified confidence bands for a simple linear regression model. *Statistical Methodology*, *3*(2), 186–192. https://doi.org/10.1016/j.stamet.2005.09.008

He, X., Sinan, M., Kwak, H., & Hoteit, H. (2021). A corrected cubic law for single-phase laminar flow through rough-walled fractures. *Advances in Water Resources*, *154*, 103984. https://doi.org/10.1016/j.advwatres.2021.103984

Iqbal, M., Ullah, Z., Khan, I. A., Aslam, S., Shaheer, H., Humayon, M., Salahuddin, M. A., & Mehmood, A. (2023). Optimizing task execution: The impact of dynamic time quantum and priorities on Round Robin scheduling. *Future Internet*, *15*(3), 104. https://doi.org/10.3390/fi15030104

Kanhere, S. S., Sethu, H., & Parekh, A. (2002). Fair and efficient packet scheduling using Elastic Round Robin. *IEEE Transactions on Parallel and Distributed Systems*, *13*(3), 324–336. https://doi.org/10.1109/71.993210

Khan, A., Zarin, R., Ahmed, I., Yusuf, A., & Humphries, U. W. (2021). Numerical and theoretical analysis of Rabies model under the harmonic mean type incidence rate. *Results in Physics*, *29*, 104652. https://doi.org/10.1016/j.rinp.2021.104652

Li, D., Wu, C., & Chang, F. M. (2005). Determination of the parameters in the dynamic weighted Round-Robin method for network load balancing. *Computers & Operations Research*, *32*(8), 2129–2145. https://doi.org/10.1016/j.cor.2004.02.004

Marcelino, F. J. G., Escubio, M. T., & Baquirin, R. B. M. (2020). A comparative analysis of quantum time based on arithmetic, geometric, and harmonic mean for dynamic round-robin scheduling. *Proceedings of 2020 6th International Conference on Computing and Data Engineering*. https://doi.org/10.1145/3379247.3379283

Mostafa, S. M., & Amano, H. (2020). Dynamic Round Robin CPU scheduling algorithm based on K-Means clustering technique. *Applied Sciences (Basel)*, *10*(15), 5134. https://doi.org/10.3390/app10155134

Ndiki, D., Helgert, H. J., & Hussein, S. (2010). A Comparative Overview IEEE 802.16e QoS Scheduling Algorithms. *A Comparative Overview IEEE 802.16e QoS Scheduling Algorithms*. https://doi.org/10.1109/internet.2010.22

Patil, N., & Aeloor, D. (2017). A review - different scheduling algorithms in cloud computing environment. *2017 11th International Conference on Intelligent Systems and Control (ISCO)*. https://doi.org/10.1109/isco.2017.7855977

Piotrowski, A., & Napiorkowski, J. J. (2019). Simple modifications of the nonlinear regression stream temperature model for daily data. *Journal of Hydrology*, *572*, 308–328. https://doi.org/10.1016/j.jhydrol.2019.02.035

Pradhan, P., Behera, P. K., & Ray, B. K. (2016). Modified round-robin algorithm for resource allocation in cloud computing. *Procedia Computer Science*, *85*, 878–890. https://doi.org/10.1016/j.procs.2016.05.278

Rout, S., Patra, S. S., Patel, P., & Sahoo, K. S. (2020). Intelligent Load Balancing Techniques in Software Defined Networks: A Systematic review. *2020 IEEE International Symposium on Sustainable Energy, Signal Processing and Cyber Security (iSSSC)*. https://doi.org/10.1109/isssc50941.2020.9358873

Semong, T., Maupong, T., Anokye, S., Kehulakae, K., Dimakatso, S., Boipelo, G., & Sarefo, S. (2020). Intelligent Load Balancing Techniques in Software-defined Networks: A survey. *Electronics (Basel)*, *9*(7), 1091. https://doi.org/10.3390/electronics9071091

Sharma, A., Kahlon, K. S., & Kumar, H. (2014). Survey of scheduling algorithms in IEEE 802.16 PMP networks. *Egyptian Informatics Journal/Egyptian Informatics Journal*, *15*(1), 25–36. https://doi.org/10.1016/j.eij.2013.12.001

Umadevi, K. S., & Chaturvedi, P. (2017). Predictive load balancing algorithm for cloud computing. *2017 International Conference on Microelectronic Devices, Circuits and Systems (ICMDCS)*. https://doi.org/10.1109/icmdcs.2017.8211727

Varalakshmi, P., Mithesh, A., Niveditha, B., G., R. P., & Yogeeswar, S. (2022). Intelligent load balancing in SDN. *2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS)*. https://doi.org/10.1109/icaccs54159.2022.9785334

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