Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7683974

A GREEN CLOUD COMPUTING MODEL FOR ENERGY-AWARE MACHINE ALLOCATIONS AND PLACEMENTS

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Abstract:
The demand for distributed computing administration has increased due to the cloud's high degree of change and adaptability. To address this, the electrical energy efficiency of cloud server farms needs to be improved more. This proposal suggests and assesses an energy-efficient half-and-half (EEH) plan to improve server farms ability to use power efficiently. Bidding reservation and staff makeup will be considered together instead of using a single technique like in analogous works that have already been proposed. The EEH structure arranges customer requests according to time and resource requirements before bookings are made. The planning decisions use accounting calculations that account for electricity use. Additionally, it contains calculations performed by the union to identify which employees need to take a break or sleep, it is overworked, it needs to transfer virtual computers, and it moves virtual machines. The EEH structure also includes a move computation that assigns new workers to move virtual machines. In terms of power utilization efficiency (PUE), data center energy productivity (DCEP), usual run time, throughput, and power consumption, the replication test results demonstrated that the EEH system was one way to reduce power consumption has demonstrated superiority over competing approaches that leverage cost savings to address.

Index Terms: Energy-Efficient half (EEH), Power Utilization Efficiency (PUE), Data Center Energy Productivity (DCEP)

I. INTRODUCTION

The majority of today's IT-based businesses use developments in distributed computing. In order to stay competitive and satisfy rising customer demand, cloud service providers like Google, Amazon, and Microsoft are consistently introducing new services to the cloud environments. Distributed computing is a developing technology to increase. A lot of businesses are also switching to cloud-based frameworks for their IT systems[1]. By 2021, 95% of computation will be carried out reliably across distributed computing frameworks. According to the International Data Corporation (IDC), by 2025, the total amount of information generated and managed would amount to 165 zettabytes[2]. Cloud service providers must thus build more offices and administration facilities.The deployment of new server farms and cloud resources as a result of these management and office kinds consumes roughly 9 degrees of electrical capacity are described in figure 1.

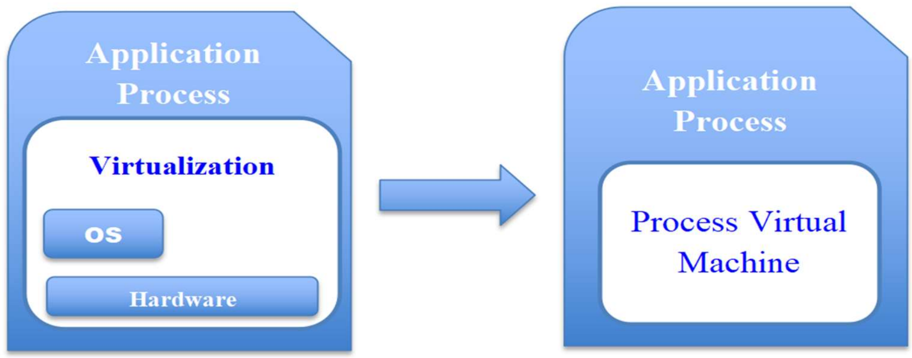

Figure 1: Architecture of Virtual Machine

Virtual machines (VMs) that have been moved to and are currently operating on server farms can be used as resources in a distributed computing framework for client management. A server farm's employees each have access to a wide range of resources[3]. As a result, each cloud contains a lot of resources that use a lot of electricity, producing undeniable CO2 emissions. By 2050, 30.9% of the world's energy demand, according to N. Jones' prediction, will be consumed by data and communications developments. It added that each year, the server farm consumes 200 terawatt hours of electricity.In the context of distributed computing, ideal green processing continues to be a hard task and a serious concern[4-5]. By addressing the fundamental patterns of suppliers, customers, and the environment, this attempts to lower operating costs and CO2 emissions.Higher power consumption rates in processing frameworks like cloud and matrix computation frameworks are the primary goal of green registration. Vision claims that the major objective of this work is to offer an energy productivity crossover fabric (EEH) to enhance server farms' capacity for power consumption.The suggested approach considers that the energy consumption of server farm components varies over time and employs both accounting and consolidation methods. To enable environmentally friendly computer management, possibly in distributed computing, it has been suggested to employ a crossover system[6]. A crucial component of construction is the art of planning and combining. Compound computations in this structure rely on variable upper and lower bound estimations of utilization, and scheduling computations take both time and power usage savings into account[7-8]. The execution of the suggested structure is assessed using CloudSim, and its results are contrasted with those of other similar methods suggested in the article.

II. CLOUD BASED DATA CENTER

It implements power management strategies and technologies in massive data centers. A local manager and a global manager make up the resource managers in the proposed policy [9-12]. The system merely takes on the guest operating system's power management policy as a local manager. The local manager provides information about the local manager's VM placement and available resources.

- **Green Data Centers: Biobjective Task Scheduling**

The server farm sector is the fifth-largest global energy consumer. Each year, Circular Green Server Farms (DGDCs) use 300 billion kWh to offer a range of services to clients all over the world. Customers from all around the world pay her DGDC provider based on the project's quality of service (QoS) management. Different Internet Service Providers send quotas to DGDC (ISPs). Data transfer rates and restrictions vary depending on the supplier[13]. Additionally, the cost of energy varies between grid, wind, and solar based on the topography of various GDCs. As a result, it is extremely challenging to arrange her DGDC allocation in a way that maximizes utility and her QoS.This effort will concentrate on the following by mutually agreeing on the task distribution across several ISPs and the task management rate of each GDC: For DGDC, devise a multifaceted promotion strategy. The issue is defined and resolved utilizing a simulated stiffening-based bio objective differential progression (SBDE) method in order to determine the approximate Pareto ideal theorem[14]. The knee location in the DGDC that displays Pareto's optimum task management rate and the distribution of businesses across his ISPs is chosen using the nearest Manhattan distance approach. In-depth studies in the actual world demonstrate that the suggested method produces better utility than previous planning computations, with an average reduction in job loss.The number of international customer projects will significantly raise the cost of DGDC's energy while also raising sales for DGDC suppliers. The final assignment receives a unique QoS assignment. Geographical disparities are also shown by many aspects in several GDCs, such as: Power Matrix and Prices for Wind and Solar-Oriented Energy[15-18]. Therefore, a meaningful test would be to collectively raise the DGDC supplier's utility and lower his ATLP for all client applications. The PQTS approach is suggested in this work to reach a fair compromise between these two goals of the two clients and her DGDC. In this proposal, a biotarget rationalization problem is defined and solved using SBDE calculations.

Information-based simulations demonstrate that, in terms of utility and ATLP for all applications, the suggested method surpasses a number of current business plan estimations. It intends to expand on our current research in the future to decompose the DGDC display using more sophisticated queuing models, such as Pareto lines. Millions of high-level workers, switches, and capacity devices that support clients all over the world in diverse ways make up distributed server farms. In essence, a startling rise in the number of missions is costing suppliers billions of dollars in electricity bills[19]. Furthermore, the energy they consume generates a considerable amount of waste from fossil fuels.Examples of strategies suggested to identify DGDC include planning. For DGDC suppliers, the issue of not being lucrative and not rigorously adhering to project type management (QoS) standards still exists. For the sake of clarity, the tasks taken into consideration in this proposal refer to the requirements for delay-sensitive standard applications as stated in the DGDC. Examples of latency-sensitive applications include web searches, intelligent web games, e-commerce, and other applications that demand lightning-fast reaction times. According to the help level agreements that the customer and supplier support, a customer's duties generate income for the DGDC supplier. As a result, lower energy consumption may result in lower client job quality.

- **Cloud and edge computing task scheduling with energy and performance**

optimization

Haitao Yuan et al. make the elegant and practical suggestion that heterogeneous applications share infrastructure resources across distributed cloud server farms. A brand-new paradigm that permits boundary determination at the end device is edge registration[20]. Uneven load distribution, lengthy scheduling, and a lack of power from the hub are some of the problems, though. Therefore, efficient project planning for CDC and edge hubs is essential for developing energy-efficient cloud and edge processing architectures. Current solutions are unable to considerably reduce the total cost of CDC, maximize efficacy, and enhance allocation quality of service due to the enterprise's heterogeneity and aperiodic nature.This display suggests a class of enhanced energy and performance design calculations based on some ingenious extension calculations. Applications that need to be postponed are being submitted by more and more businesses. To control a lot of data, deep learning, and sophisticated registration to different cloud server farms. These apps collaborate on CDC framework resources and offer different kinds of client support in a very economical way. This ultimately results in an increase in the energy used by these enormous server farms[21]. A continuous and flexible information transmission border is provided by edge registration as an evolving design, although it has some drawbacks due to handling and battery restrictions.Therefore, it is essential to allocate resources and schedule tasks effectively at the CDC and edge hubs in order to control energy usage and costs. Ecology, economic viability, energy efficiency, and binding confirmation, however, are very difficult to put off due to emotional growth, aperiodic appearance, and varied initiatives. After that, this proposal suggests that in order to address the issues brought on by appropriate cloud and edge registry systems, intelligent job scheduling and resource allocation computations should be further developed.

- **Management of cloud data center energy consumption and overloaded hosts with adaptive heuristics**

Rahul Yadav et al. make a solution for the issue of excessive power usage and SLA violations in cloud systems in this paper. Most earlier research suggests cloud data center (CDC) methods to handle energy usage and SLA violations, but neglects a number of crucial elements[21].

a. Check the stability of the high CPU utilization threshold to ensure optimal resource use.
b. To prevent performance degradation and SLA violations, choose VMs from overloaded hosts based on projected CPU utilization.

In this context, it has created two of his adaptive heuristic methods: least median squares regression for overloaded host identification and minimal load prediction for his VM selection of overloaded hosts. These heuristic techniques minimize SLAs while reducing CDC power usage.In contrast to current methods, the suggested VM selection technique considers the types of apps running and their CPU consumption across VMs at various times. The suggested approach is examined by recreating actual workload traces from PlanetLab across a number of days in the CloudSim simulator. Globally, the rapid growth of CDCs is driving up CO_2 emissions and huge power usage[22]. The focus of our proposal is on cloud IaaS platforms in two ways. Reducing overall power consumption is the first step because it has an immediate impact on CDC running costs. As a result, this proposal offers a real environment for the global development of the cloud computing sector. Second, fewer host and VM migrations, hosts that can run, and SLA violations. Additionally, a new method of congested host detection called LmsReg and a strategy for choosing VMs from congested hosts called MuP are suggested. The suggested approach is put into practice using a CloudSim simulator. According to experimental findings, these methods greatly lower CDC's power usage when compared to earlier crowded host detection and VM selection techniques. They install the proposed algorithms on an open source cloud computing platform called Open-Stack and assess the outcomes to determine how well they perform on actual cloud computing systems[23]. It also looks at cutting-edge machine learning methods like: B. Decline in gradient.As part of the SLA, new strategies for lowering data center energy use are also being explored.Construction of enormous data centers was required due to the exponential growth in demand for computing power. These data centers must use a significant amount of electricity to deliver vital services to cloud users, raising operational expenses and their carbon impact. Data centers use 1.3% of the electricity produced globally, according to statistics, and by 2020, this percentage is predicted to increase by 10%.

- **Energy-Efficient Nature-Inspired techniques in cloud computing data centers**

Mohammed JodaUsman and colleagues in this proposal suggest cloud computing, a service that involves the routine delivery of computing resources to users over the Internet[24]. IaaS (Infrastructure as a Service) makes it easier for users to access processing, storage, networking, and other essential computer resources, allowing them to deploy and execute any software, including operating systems and applications. Virtual machines may also be made available as resources. Customers are charged accordingly and given cloud services as needed. Virtual machines frequently use a lot of energy, generate dangerously high levels of carbon dioxide into the atmosphere, and operate in several data centers with various computer resources.One such answer is an algorithm with naturalistic design [24]. To that aim, this white paper offers a thorough examination of cutting-edge, naturally inspired algorithms suggested for resolving cloud data center power issues. The three main areas of the literature are categorized according to a taxonomy that focuses on virtualization, integration, and energy perception. Each approach is qualitatively assessed taking into account its primary goals, approach, strengths, and shortcomings. It contrasts the characteristics of algorithms drawn from nature to demonstrate how efficiently they use resources and how much energy they require[24]. Then specify future research objectives for data center energy optimization. This evaluation aids researchers studying cloud computing data centers and business experts in their understanding of the literature that is developing for more energy-efficient methods.

This Proposal examined frequently employed methods, methodologies, tools, and tactics that were drawn from nature in order to lower energy consumption in cloud computing data centers. The objectives, tactics, advantages and disadvantages of the methods under consideration were discussed. It also looked at the properties of the researched algorithms to identify each one's unique energy efficiency[25]. These solutions have a number of shortcomings while being effective across different IaaS levels, according to evaluations. The majority of scheduling techniques used today rely heavily on cloud data centers for electricity. These methods utilize resource allocation algorithms that consume a lot of electricity since they take so long to converge. Current approaches obviously ignore the network component, which consumes the majority of energy in data centers. Infrastructure in data centers that isn't being used to its full potential wastes energy. SLAs were not working when attempts were made to cut energy use, according to an analysis of the method. In order to efficiently and proactively increase the energy efficiency and resource utilization of cloud data centers, new methods must be developed due to the drawbacks of existing ones. Such techniques ought to be developed to control resource and energy waste, taking into account the power requirements of network hardware and input/output devices[25]. In order to ensure ecological sustainability and lessen adverse effects on human existence, it is possible to drastically cut global carbon emissions in this way.

- **Cloud computing with adaptable energy-aware algorithms to minimize energy consumption and SSA violations**

Since the power need of computing is increasing quickly and demands large cloud server farms, high power consumption and SLA violations are major problems in distributed computing. However, many existing power-conscious strategies ignore SLA violations when a virtual machine (VM) detects overload in favor of minimizing power usage[26]. Due to the ignorance of how present organizational flows affect execution, many of the responsibilities might not even minimize SLA violations. This white paper suggests three adaptable models that, when used under particular circumstances, can successfully lower energy usage and SLA violations. These models include data transfer capacity, relation rate, and propensity-dependent recurrence (Gdr, MCP) (Bw). Energy-aware techniques for identifying congestion and choosing VMs away from congestion are essential for reducing energy productivity and SLA breaches in cloud server farms. Moving all virtual machines from overload to sleep state has other advantages[26-27]. Strong fallback models underlie the flexible energy-aware calculations Gdr and MCP, which enable overload identification. According to network traffic from overloads placed under a SLA, the Bw dynamic VM selection mechanism chooses VMs.To increase energy efficiency and decrease SLA violations in foggy situations, calculations with consideration for energy are advised. The game's outcome demonstrates that:

a. Gdr overload detection calculations are more energy productive than MCP calculations.
b. When calculating VM congestion, including your organization's CPU, memory, and traffic components is more beneficial than considering just one factor, such as CPU[28].

Regardless of the responsibility category, the calculations reported in this study are more convincing than other energy-conscious computations. They intend to suggest a thermally conscious estimate of VM placements in the future. Additionally, it details the reductions in activity costs, SLA breaches, and energy productivity.

III. EXISTING SYSTEM

For VM planning, it is crucial to make reservations using asset check data that is isolated from past asset consumption (counting PMs and VMs) and asset data defined using the K-NN and NB extension methods. demonstrates a way of thinking. Ordinal models make an effort to infer meaning from observed characteristics. In order to forecast the value of at least one result given at least one source of information, an ordering model must be used. Results are the notations it can make on your records. AI can be controlled either manually or autonomously. The control model's placement computations take into account the preparation data records. K-nearest neighbor (k-NN) computation is a nonparametric method used for characterisation and fallback are described in figure 2.

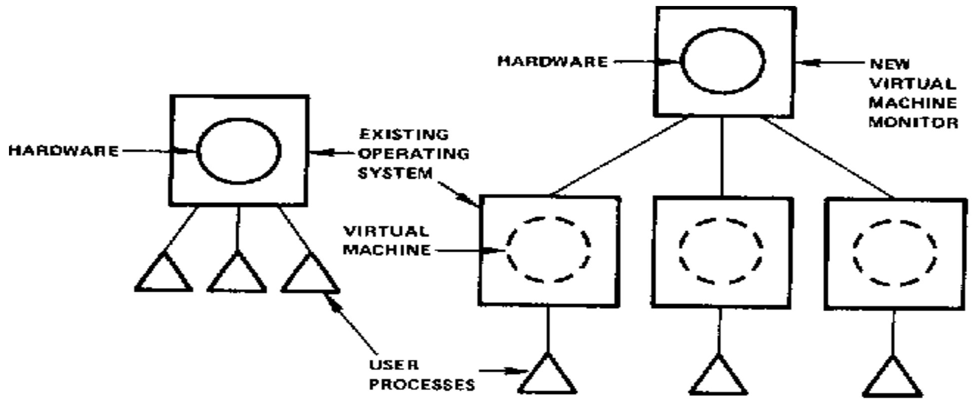

Figure 2: Operating System Encapsulated in a Virtual Machine

Performance monitoring for virtual servers should differ from that for physical servers. Memory and CPU consumption cannot be measured using conventional techniques. Hardware resources that are shared by all of the VMs in your virtual infrastructure include CPU, memory, and storage. When a host can accommodate hundreds of virtual machines, each VM can process data concurrently by sharing some of the resources explained in figure 3.

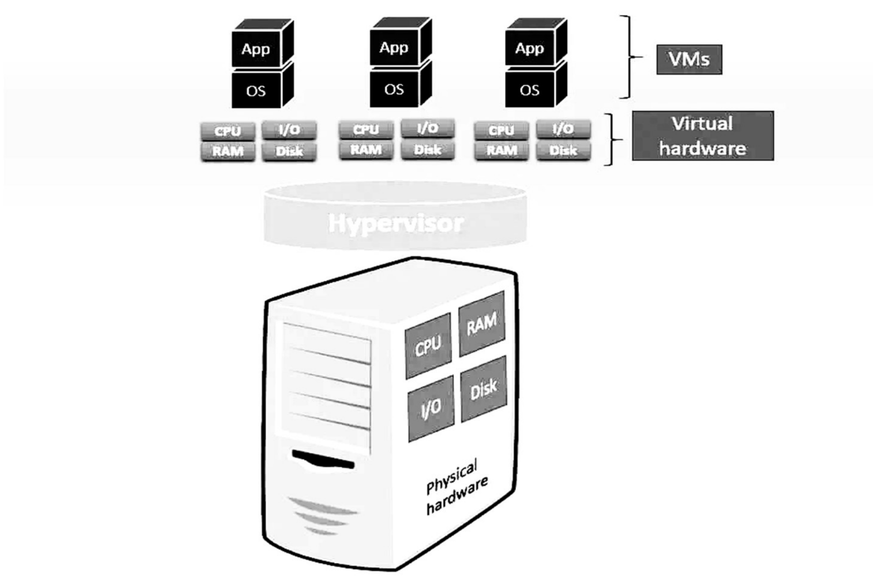

Figure 3: Hardware of Virtual Machines

It needs to thoroughly examine a set of key performance indicators to make sure virtual infrastructure is operating as intended. Real-time monitoring of all VMs is necessary for metrics like CPU and memory readiness, memory bubble detection, and memory switched out. The monitoring process is made more difficult by live VM broadcasts.

IV. PROPOSED SYSTEM

The concept of scheduling VMs based on monitoring data from previous auxiliary usage is put forth, and historical VM utilization levels are combined with K-NN and NB to plan VMs while maximizing overall performance. can be looked at. The suggested VM scheduling method concludes a section of VM selection that is totally dependent on the gathering of tracking data in real-time and the assessment of physical and digital resources. To improve VM planning to include criteria relating to actual VM usage levels in order to locate VMs with the fewest penalty at typical performance levels.To maximize use levels and reduce overall performance loss, the optimization approach analyzes existing installed VMs. Due to the underuse of the VM, the user does not consistently use Aid throughout the day. Because of cloud control activities and VM placement, for instance, appropriately loaded VMs frequently take CPU instances from surrounding VMs, which can lead to subpar database cluster performance. These straightforward illustrations highlight the need for a more advanced VM scheduling mechanism that boosts overall performance.

Physical computers have been chosen for scheduling using various digital device placement methods based on device metadata (such as CPU, memory, and bandwidth usage in cloud systems). The default VM location does not retain real-time VM aid utilization levels. The fresh set of recommendations for VM placement based on previous VM utilization statistics is put out. The data is then educated using machine learning models (K-NN NB) to predict VM support utilization and arrange VMs accordingly. The VM utilization is then tracked.A computational learning technique based solely on the idea of learning beyond VM support use in line with past acts to optimize the PM choice segment was also delivered.

A. VM Scheduling

Policies collect real-time tracking data, assess physical and digital assets, and improve the VM selection section. The proposal is to enhance VM scheduling as shown in figure 4. It must provide guidelines for actual VM utilization levels in order to localize VMs.

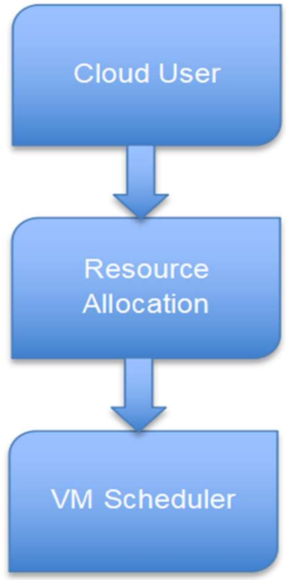

Figure. 4 VM Scheduling

Utilizing a tool for internet tracking that provides VM utilization data, the optimization approach analyzes already provisioned VMs to maximize utilization windows and reduce overall performance loss. In order to gather device data and store it in a web cloud service for data processing, the engine can use the C programming language. Every tiny bit of time, the C programming language gathers data and stores it in a temporary neighborhood file.

B. Classification Algorithm

The input data set must be labeled before using a supervised machine learning algorithm for classification.

K-Nearest Neighbor's Method: K-Nearest Neighbors is a straightforward method for categorizing new cases and maintaining all of the current cases using a similarity metric. K-NN was utilized for both statistical inference and pattern recognition. Nonparametric approaches, such as k-nearest neighbor (k-NN) algorithms, are used in classification and regression are in figure 5.

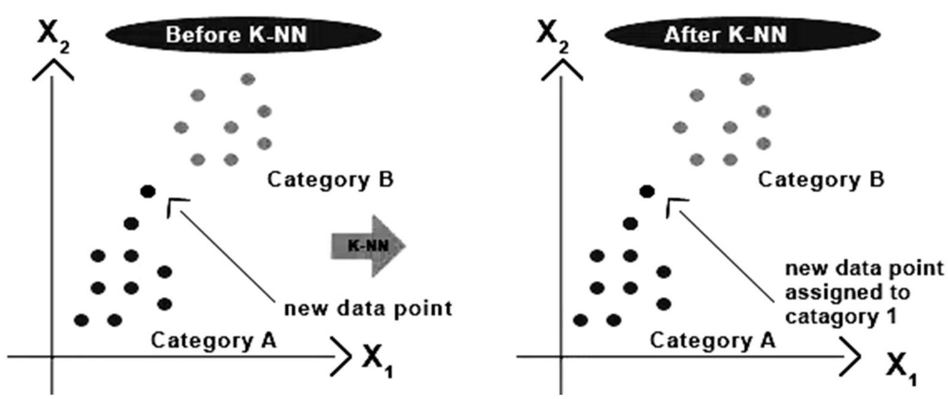

Figure 5: K-NN Algorithm

Naive Bayes (NB) method: Naive Bayesian classification is frequently employed when the input data is highly dimensional and primarily relies on Bayes' theorem. Based only on their inputs, Bayesian classifiers are effective at determining the most useful output. More probabilistic classifiers may also be utilized to upload new raw data when it is needed. Naive Bayesian classifiers make the assumption that the existence (or lack) of one categorical feature (attribute) is independent of the presence (or absence) of another feature in the presence of grand factors.A naive Bayesian classifier assumes that each of these characteristics will independently increase the likelihood that the fruit is an apple, yet these characteristics depend on one another or on the distribution of other characteristics across the category to increase are explained in figure 6.

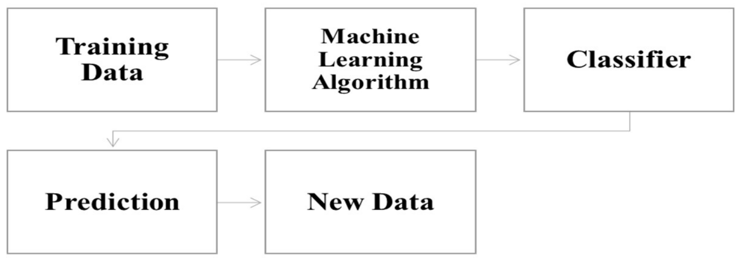

Figure 6: Overview of NB Classifier

C. Optimization Scheme

This optimization strategy aims to define the workload of the PM in terms of how the VMs are using their resources as shown in figure 7. This will show details about the condition of provisioned VMs. The movement of the workload offers an optimization technique. Here, categories of recognized VMs are rated for their current resource use based on the presented KNN and NB.

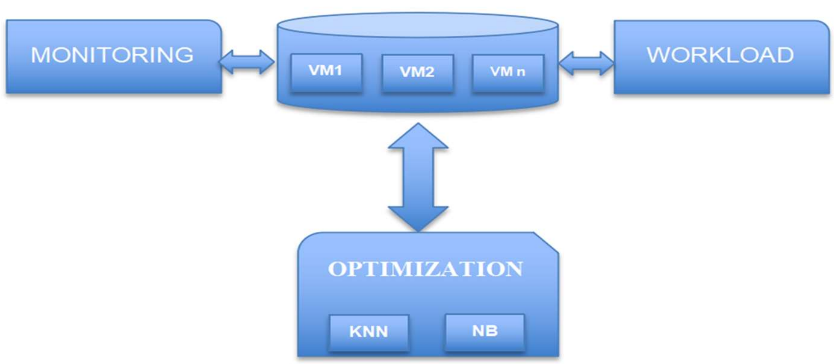

Figure 7: Optimization in VM

V. SIMULATION RESULTS

Cloud Sim, an open source tool for creating both private and public clouds, is the main topic of the proposal. Until the allotted amount of memory is reached, VMs are installed in the default Cloud Sim configuration by picking the host with the most memory available. Such behavior overloads effective PMs in the stack while ignoring RAM-poor PMs. Additionally, by creating a machine learning model that quickly evaluates how often PMs and VMs use support, help analytics is entirely dependent on how often people use it. Without taking into account average and long-term consumption, virtual machines (VMs) are allocated to hosts based on their immediate resource usage, such as the host with the greatest RAM. Additionally, planning and placement techniques are frequently computationally demanding, which affects how well deployed VMs function as a whole. The mean absolute error and relative absolute error for the virtual machine allocation and placement are depicted in figure 8 and figure 9.

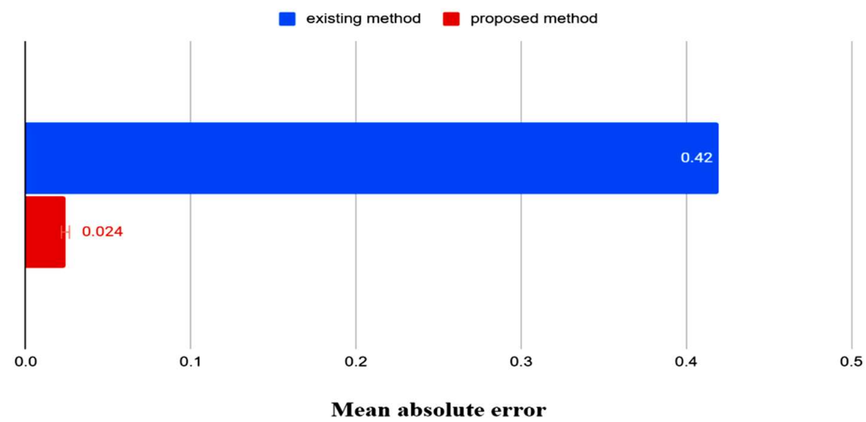

Figure 8: Mean Absolute error in VM allocation

As a result, the high hierarchy of VM support utilization is no longer taken into account by traditional VM placement rules. This VM scheduling issue is resolved by a set of rules. From Beyond-Aid usage (including PM and VM), where help data is categorized and scheduled using K-NN and NB optimization algorithms, VM scheduling concepts that are consistent with help tracking data are applied. Policy collections are evaluated across deployment levels and ranked according to overall supportive deployment. Assets are prioritized according to task when a list of suitable hosts is entered.When the task takes place, assets are arranged in accordance with the list of requested hosts. More specifically, using this set of policies, PMs are re-ranked based solely on VM consumption and in accordance with the selected optimization approach. Use seven-day tracking of assistance usage as an example, and twenty-four-hour tracking of help facts as the fact set. The analysis is in line with (a) usage levels over time and (b) data upkeep by classifying usage over time into low, medium, and high. They employ a weighting strategy that is compatible with the selected PM discriminator in this guide.

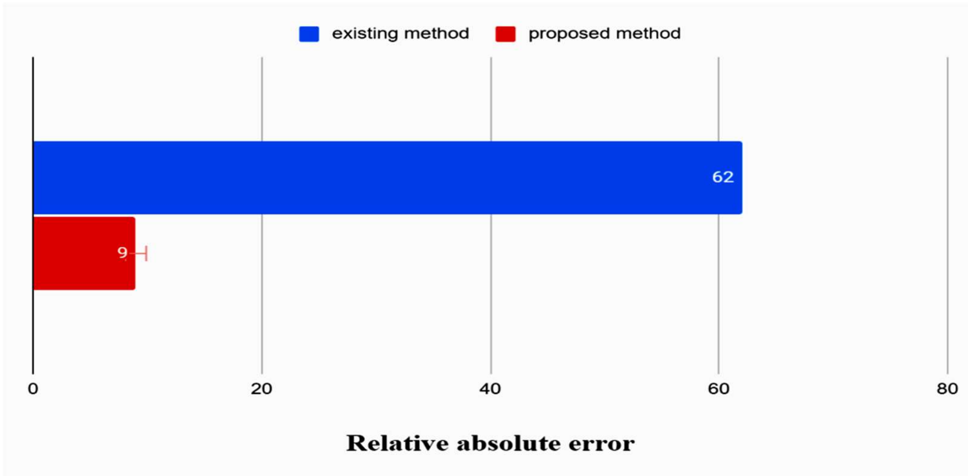

Figure 9: Relative Absolute error in VM allocation

VI. CONCLUSION

A set of VM placement guidelines based on real-time monitoring of digital help was also provided. These guidelines used device learning models to study and learn from past data on how digital device resources were used. As a result, information on help utilization is used to build a tracking system. The reliance on the physical device is decreased by using the KNN & NB classifier instead of the Support Vector Machine (SVM) classifier. The 54 physical devices were used to complete the work, and by employing the KNN& NB classifier set of rules instead of SVM, 54 physical devices were saved, resulting in a 0.024% reduction in mean absolute error. The recommended model makes it possible for data processing to accurately identify the PMs' or VMs' actual behavior over the course of a time period. The VM placement approach's end result amply demonstrates the major advantages. In order to increase performance, future research can be conducted with additional experimentation that is pertinent to other system learning models, such as random forests and selection trees.

REFERENCE

1. Buyya, R.; Yeo, C.S.; Venugopal, S.; Broberg, J.; Brandic, I. Cloud computing and emerging IT platforms: Vision, hype, and reality for delivering computing as the 5th utility.
2. Fox, A.; Griffith, R.; Joseph, A.; Katz, R.; Konwinski, A.; Lee, G.; Stoica, I. *Above the Clouds: A Berkeley View of Cloud Computing*; Department of Electrical Engineering and Computer Sciences, University of California, Berkeley: Berkeley, CA, USA, 2009.
3. Luo, J.; Li, X.; Chen, M. Hybrid shuffled frog leaping algorithm for energy-efficient dynamic consolidation of virtual machines in cloud data centers. *Expert Syst. Appl.* 2014, *41*, 5804–5816.
4. Kaplan, J.M.; Forrest, W.; Kindler, N. *Revolutionizing Data Center Energy Efficiency*; Technical Report; McKinsey & Company: New York, NY, USA, 2008.
5. Barroso, L.A.; Holzle, U. The case for energy-proportional computing. *Computer* 2007, *40*, 268–280

6. Clark, C.; Fraser, K.; Hand, S.; Hansen, J.G.; Jul, E.; Limpach, C.; Pratt, I.; Warfield, A. Live migration of virtual machines. In Proceedings of the 2nd Conference on Symposium on Networked Systems Design & Implementation–Volume 2, USENIX Association, Boston, MA, USA, 2–4 May 2005; pp. 273–286.
7. Voorsluys, W.; Broberg, J.; Venugopal, S.; Buyya, R. Cost of virtual machine live migration in clouds: A performance evaluation. In Proceedings of First International Conference, CloudCom 2009, Beijing, China, 1–4 December 2009; pp. 254–265.
8. Nathuji, R.; Schwan, K. VirtualPower: Coordinated power management in virtualized enterprise systems. *ACM SIGOPS Oper. Syst. Rev. ACM* 2007, *41*, 265–278.
9. Kusic, D.; Kephart, J.O.; Hanson, J.E.; Kandasamy, N.; Jiang, G. Power and performance management of virtualized computing environments via lookahead control. *Cluster Comput.* 2009, *2*, 1–15.
10. Verma, A.; Ahuja, P.; Neogi, A. pMapper: Power and migration cost aware application placement in virtualized systems. In Proceedings of ACM/IFIP/USENIX 9th International Middleware Conference, Leuven, Belgium, 1–5 December 2008; pp. 243–264.
11. Verma, A.; Dasgupta, G.; Nayak, T.K.; De, P.; Kothari, R. Server workload analysis for power minimization using consolidation. In Proceedings of the 2009 Conference on 12. USENIX Annual Technical Conference, USENIX Association, San Diego, CA, USA, 14–19 June 2009; p. 28.
12. Forsman, M.; Glad, A.; Lundberg, L.; Llie, D. Algorithms for automated live migration of virtual machines. *J. Syst. Softw.* 2015, *101*, 110–126.
13. Song, W.; Xiao, Z.; Chen, Q.; Luo, H. Adaptive resource provisioning for the cloud using online bin packing. *IEEE Trans. Comput.* 2014, *63*, 2647–2660.
14. Huang, C.J.; Guan, C.T.; Chen, H.M.; Wang, Y.W.; Chang, S.C.; Li, C.Y.; Weng, C.H. An adaptive resource management scheme in cloud computing. *Eng. Appl. Artif. Intell.* 2013, *26*, 382–389.
15. Islam, S.; Keung, J.; Lee, K.; Liu, A. Empirical prediction models for adaptive resource provisioning in the cloud.
16. Kinger, S.; Kumar, R.; Sharma, A. Prediction based proactive thermal virtual machine scheduling in green clouds. *Sci. World J.* 2014.
17. Beloglazov, A.; Buyya, R. Optimal online deterministic algorithms and adaptive heuristics for energy and performance efficient dynamic consolidation of virtual machines in cloud data centers.
18. Fu, X.; Zhou, C. Virtual machine selection and placement for dynamic consolidation in Cloud computing environment.
19. Murtazaev, A.; Sangyoon, O. Sercon: Server consolidation algorithm using live migration of virtual machines for green computing. *IETE Technol. Rev.* 2011, *28*, 212–231.
20. Beloglazov, A.; Abawajy, J.; Buyya, R. Energy-aware resource allocation heuristics for efficient management of data centers for cloud computing.

21. Calheiros, R.N.; Ranjan, R.; Beloglazov, A.; Rose, C.A.; Buyya, R. CloudSim: A toolkit for modeling and simulation of cloud computing environments and evaluation of resource provisioning algorithms.
22. Park, K.S.; Pai, V.S. CoMon: A mostly-scalable monitoring system for PlanetLab. *ACM SIGOPS Oper. Syst. Rev.* 2006, *40*, 65–74.
23. Horri, A.; Mozafari, M.S.; Dastghaib Fard, G. Novel resource allocation algorithms to performance and energy efficiency in cloud computing. *J. Supercomput.* 2014, *69*, 1445–1461.
24. R. H. Michael, D. Umesh, and G. Kartik 2009. Post-copy live migration of virtual machines. ACM Special Interest Group on Operating Systems, pp14-26.
25. L. Weining and F. Tao 2009. Live migration of virtual machine based on recovering system and CPU scheduling. 6th IEEE joint International Information Technology and Artificial Intelligence Conference,Piscataway, NJ, USA, 303- 208
26. L. Haikun, J. Hai, L. Xiaofei, H. Liting, and Y. Chen, , 2009. Live migration of virtual machine based on full system trace and replay. 18th ACM International Symposium on High performance distributed computing, pp 101-110.
27. Soramichi Akiyama, Takahiro Hirofuchi, Ryousei Takano and Shinichi Honiden, “MiyakoDori: A Memory Reusing Mechanism for Dynamic VM Consolidation”, 2012 IEEE Fifth International Conference on Cloud Computing
28. Arun Babu Nagarajan, Frank Muller, Christian Engelmann, Stephen L.Scott 2007. Proactive fault tolerance for HPC with Xen Virtualization. Proceedings of the 21st annual international conference on supercomputing.