International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

Enhanced Particle Swarm Optimization Algorithm for Cloud Computing Environments Workload Scheduling

Zeenath Sultana[1], Dr. Raafiya Gulmeher[2], Asra Sarwath[3]
[1,2,3]Assistant Professor, Dept. of CS&E, Khaja Bandanawaz University, Kalaburagi, Karnataka, India.
Emails: *zeenathh@kbn.university[1], raafiya@kbn.university[2], sarwath@kbn.university[3]*

Abstract
Because of cloud services' increased accessibility, enhanced performance, and affordability, cloud service providers are always looking for ways to speed up work completion in order to increase revenues and save energy costs. Even though many scheduling algorithms have been developed, many of these methods only focus on one aspect of the scheduling process. An innovative method called the Enhanced Particle Swarm Optimisation Algorithm (EPSOA) is put forward to effectively improve optimisation outcomes for the cloud workload scheduling issue. The PSO and the Lévy flight are integrated by EPSOA. The purpose of adding Lévy combat is to increase the PSO's search space and speed up convergence via adaptive crossover. The Cloudsim program is used to simulate and assess the EPSOA model under various test scenarios. By using a variety of factors and contrasting them with those of current algorithms, the efficacy of EPSOA is evaluated. The results show that EPSOA performs better than other algorithms in terms of execution cost, energy consumption, and resource usage, demonstrating its effectiveness in managing the difficulties associated with multi objective cloud job scheduling.

Keywords: *Scheduling, Cloud computing (CC), Resource allocation (RA), Adaptive crossover, Lévy flight.*

1. Introduction
From individuals to major corporations, CC is a cutting-edge computational framework that serves a broad range of users [1]. The core of CC is made up by expensive and complex data centres (DCs), which have a big influence on service providers' capacity to make ends meet [2]. Using web service technology, cloud service providers provide three main service categories: Infrastructure as a Service (IaaS), Software as a Service (SaaS), and Platform as a Service (PaaS) [3]. In the increasingly competitive cloud industry, cloud providers must strike a balance between effectively controlling their Total Cost and providing their computing resources to satisfy customers' Quality of Service (QoS) requirements [4]. In data centres, virtualisation technology is crucial for optimising RA and reducing total power usage, which is a crucial component of TCO. Strategies for electricity management also support sustainability goals. In a virtualised environment, a hypervisor distributes the resources of Physical Machines (PMs) across Virtual Machines (VMs). Insufficient RA has a negative effect on data centres total power consumption as well as resource utilisation [5]. Because it entails distributing user work across many virtual machines in order to achieve certain goals, resource scheduling is a major difficulty in CC [6]. An efficient scheduling strategy is needed to distribute incoming tasks to the right virtual machines (VMs) in light of the small number of VMs with different capabilities. Due to resource limitations and a variety of customer expectations, the scheduling issue is notoriously difficult and classified as an NP-hard problem [7, 8]. To address this problem, a variety of heuristic and meta-heuristic approaches have been put forward, each with a distinct set of goals. Heuristic approaches were first presented to solve the scheduling issue. Numerous scheduling methods in CC are made to target certain goals, such cutting down on energy use, optimising resource use, or minimising job completion time. For instance, some algorithms prioritise RA efficiency above task completion time, while others just examine task scheduling without taking resource utilisation optimisation into account. Furthermore, there are scheduling strategies designed especially for certain application areas, such multimedia processing

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

or scientific computing, which may have particular needs and limitations. As a result, even though there are many different scheduling algorithms, Instead of providing a comprehensive solution that considers all objectives at once, they often concentrate on a separate aspect of the resource scheduling problem. The ability of current scheduling algorithms to handle complicated scheduling problems and optimise many goals at once is often limited. Numerous conventional heuristic techniques mostly depend on preset protocols; this can provide less-than-ideal outcomes and not transfer well to large-scale applications. Similar to this, meta-heuristic approaches have shown promise in solving complex optimisation problems; but, if control parameters are not properly set, they may suffer from issues including entrapment in local optima, reduced convergence, and high memory use. The EPSOA targets applications in a variety of disciplines and job kinds, offering a fresh method for resolving the difficulties associated with CC resource scheduling. In order to overcome these limitations and offer a hybrid approach that leverages the benefits of both heuristic and meta-heuristic approaches, Te EPSOA combines state-of-the-art techniques such as Lévy fight to increase the search space and enhance convergence, enabling improved efficiency and effectiveness of scheduling in CC environments. To improve solution quality, the majority of heuristic approaches, especially when dealing with large-scale applications, mostly depend on predetermined processes. However, meta-heuristic approaches have shown to be more successful in resolving a variety of challenging optimisation issues that arise in real-world situations. However, these algorithms are inherently flawed. For example, poor control parameter tuning may result in increased memory use, decreased convergence under iterative settings, and entrapment in local optima. Hybridising one or more heuristic and meta-heuristic approaches is a potential study topic to solve these shortcomings. This strategy minimises the drawbacks of various methods while maximising their advantages. Lévy combat is used in EPSOA, a PSO variant, to effectively address multi-objective scheduling problems. When combined with the adaptive crossover approach, the integration of Lévy combat expands the PSO search space and speeds up convergence. By using a Lévy battle mechanism, The EPSOA is particularly designed to effectively address multi-objective scheduling problems. The PSO may investigate a greater variety of solutions because to the incorporation of Lévy combat, which broadens its search field. By doing this, EPSOA may optimize many goals at once, including cutting down on energy use, increasing resource utilization, and minimizing job completion time. Additionally, By using an adaptive crossover approach, EPSOA enhances its ability to converge towards the optimal solutions for the difficult scheduling problem. EPSOA stands out as a practical approach to accomplishing the many interconnected objectives that resource scheduling in CC systems entails.

2. Literature Survey

Zhang et al. [9] effectively addressed uncertainty by separating ambiguous variables into interval parameters. Throughout the intricate scheduling procedure, crucial factors including make-span, work load balance, completion rate, and scheduling cost must be considered. A new algorithm known as Interval Multi-Objective Cloud Task Scheduling Optimisation (I-MCTSO) was developed as a result of this thorough approach. This algorithm has been carefully crafted to replicate the complexities of actual CC task scheduling situations. A novel Interval Multi-Objective Evolutionary method (InMaOEA) was developed in order to put this strategy into practice. A unique interval credibility technique was used to include a creative way to improve convergence performance. In addition, the interval congestion distance approach was used with overlap and hyper-volume evaluations to increase population variety. Empirical simulations demonstrated the in MaOEA algorithm's high effectiveness and superiority over other algorithms that were previously in use. The framework offered by these proposed methods offers decision-makers a strong set of rules for allocating cloud job scheduling, enabling them to make wise decisions. These developments represent an important step forward in CC resource management, which might improve operational efficacy and efficiency. By using heuristic approaches, Alsaidy et al. [10] presented a novel improvement to the Particle Swarm Optimization (PSO) algorithm's initialization procedure. The PSO

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

algorithm's initialization phase strategically incorporates the Longest Job to Fastest Processor (LJFP) and Minimum Completion Time (MCT) algorithms. The main goal of this novel strategy is to increase the PSO algorithm's overall efficiency. A thorough analysis of the developed MCT-PSO and LJFP-PSO algorithms includes a number of important measures. These measures include minimizing makespan, lowering total execution time, reducing overall energy use, and mitigating imbalance. These metrics are essential standards for evaluating how well the suggested algorithms perform in the task scheduling domain. Extensive simulations are used to show that the proposed MCT-PSO and LJFP-PSO techniques are much better and more effective than other modern task scheduling algorithms and conventional PSO methods. These results highlight how these improvements might greatly improve task scheduling techniques [11] based on the PSO algorithm's optimization capabilities, which would greatly advance the development of effective and efficient CC resource management. Additionally, the makespan findings show significant improvements of 5–12%, while the total cost factor shows improvements of 2%–10%. The rate of energy consumption has also increased significantly, rising between 1 and 9%. The Enhanced Sunflower Optimization (ESFO) algorithm was presented by Emami [12], study's technique demonstrates its capacity to accomplish optimum scheduling with polynomial time complexity. To determine its advantages and disadvantages, the suggested ESFO technique is thoroughly examined and put through a series of work scheduling benchmarks. The results of simulation experiments demonstrate how well the ESFO algorithm performs when compared to other algorithms. It is clear that the algorithm is quite effective at optimizing job scheduling results, as seen by its strong performance across important criteria including make span and energy consumption. This technology development improves task scheduling techniques, perhaps leading to increased system efficiency and better RA. To improve scheduling efficiency, Gong et al. [13] presented the Enhanced Marine Predator Algorithm (EMPA). The suggested process includes a number of crucial steps. It entails creating a task scheduling model that takes resource use and makespan into account. Finding the best scheduling solution is the main goal of the algorithm, where each entity represents a possible task scheduling result. The EMPA incorporates many elements from the Particle Swarm Optimization Algorithm (PSO) to improve its performance, including operator functions, the golden sine function, and nonlinear inertia weight coefficients. These comparisons occur in a variety of contexts, taking into account different workloads in both simulated and GoCJ datasets. The EMPA algorithm's benefits are shown by the empirical assessment, which reveals noteworthy strengths in makespan, degree of imbalance, and resource utilization. Thus, our findings contribute significantly to the area of scheduling techniques and might improve resource management across a range of applications. [1-5]

3. Problem Statement

One of the biggest challenges in CC is assigning user workloads to accessible virtual machines (VMs) in a cloud data centre. Individual servers may run many virtual machines (VMs) simultaneously in this environment. The data centre broker controls and monitors the distribution of user tasks and directs the scheduling process. Figure 1 shows the schematic depiction of the scheduling procedure. First, cloud users submit tasks, which are then saved in the task management module. This module keeps track of incoming tasks and notifies the appropriate users of pertinent status changes. These task requests are then sent to the cloud scheduler via the task manager. To allocate incoming workloads to available virtual machines, the cloud scheduler uses the suggested EPSOA scheduling algorithm. The work requirements retrieved from the cloud information system and virtual machine information are used to establish this allocation. To meet resource needs, the public cloud system concept includes many data centers. Consider a collection of data centers with the following labels: dc1, dc2,..., dcp. There are several Physical Hosts (PHs) in every data centre. Data Centre DCR, for example, contains k PHs that are labeled as (PHr1, PHr2,..., PHrk). A PH's processing capacity, expressed in Million Instructions Per Second (MIPS), is determined by its unique features, such as the number of cores. Additionally, a VM

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

Manager (VMM) is installed on each PH, along with bandwidth, memory, and storage capacity. The VMM that is placed on PHs is essential for managing and keeping an eye on every virtual machine that is housed on that specific physical host. For the virtual machines operating on the host, it guarantees effective resource allocation and utilization. A group of m virtual machines (VMs), Figure 1 shows Scheduling Process

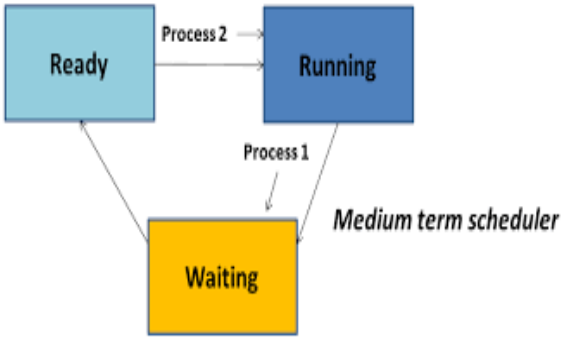

Figure 1 Scheduling Process

represented as (VM1,VM2,...,VMm), may be housed in each PH of a data centre. Every virtual machine has the following unique configurations: Several data centres that are intended to satisfy various resource requirements make up the public cloud system paradigm. Several Physical Hosts (PHs) are housed in these data centers, which are designated as dc1, dc2,..., dcp. Data centre dcr, for example, consists of k PHs designated as (PHr1, PHr2,..., PHrk). Specific characteristics, including the amount of cores, define each PH's computing capability, which is expressed in MIPS. Every PH also has memory, bandwidth, and storage space, and it has a VMM that is in charge of monitoring and controlling all virtual machines that are housed. Every PH in each data centre may support a group of m virtual machines (VMs), which are denoted by the letters VM1, VM2, VMm. Every virtual machine is set up with certain characteristics, such as Main memory: Set aside for data storage and program execution within the virtual machine. Storage: The amount of space allotted for keeping VM-specific files and data. Processing power: Shown in MIPS, this figure denotes the computer's capacity to carry out tasks and carry out instructions. Several cores: specifies the number of cores allocated to the virtual machine (VM), which establishes the VM's capacity to manage concurrent workloads and parallel processing. [6-10]

4. Proposed Methodology

The proposed approach for identifying cyber network threats using an optimization strategy was tested in MATLAB, and the results are recorded. Multi-objective optimization gains a great deal from the combination of adaptive crossover and Lévy battle in EPSOA. By permitting big, rare steps in the search space, Lévy fight, a stochastic search technique modeled after the combat patterns of foraging animals, allows EPSOA to investigate a greater variety of solutions. This exploration mechanism makes it easier to find a variety of possibly better solutions and keeps EPSOA from being trapped in local optima. Furthermore, EPSOA's capacity to strike a balance between exploration and exploitation during the optimization process is improved by the adaptive crossover technique. By constantly modifying the crossover rate in response to the optimization's progress, EPSOA may efficiently adapt its search method to the changing features of the issue terrain. This improves convergence and overall performance when addressing multi-objective optimization challenges. All things considered, the combination of adaptive crossover and Lévy combat enables by effectively navigating the complex trade-offs inherent in multi-objective optimization issues[14], EPSOA ultimately yields a more dependable and efficient solution. The PSO draws inspiration from whales' foraging habits, especially humpback whales' hunting techniques [15]. Three foraging behaviour that mimic humpback whale behavior is used in this algorithm: encircling prey, attacking with bubble nets, and pursuing prey at random. The hunting strategy of the whales is represented by mathematical modeling of this behaviour. The capacity to identify swarms exhibit this behavior by finding nearby prey and positioning themselves according to the prey location being the optimal position for the group. They constantly shift places as they get closer to the prey. The algorithm considers the produced feasible solutions as "whales" in the context of PSO and determines that the ideal location for surrounding prey is the current best solution, also known as the local optimum. The

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

program uses an operator, shown in Eq. 1, that mimics the process of surrounding prey.

$$\vec{X}(t+1) = \vec{X}_{best}(t) - \vec{A}.|\vec{C}.\vec{X}_{best}(t) - \vec{X}(t)| \text{ ---1}$$

In Eq. 1, X denotes the chosen search swarm, $|\vec{C}.\vec{X}_{best}(t) - \vec{X}(t)|$ denotes the distance between C and X best(t), and signifies an element-wise multiplication(t) that reflects a whale's best position in the current iteration t.

$$\vec{A} = 2 * \vec{a} * \vec{r} - \vec{a}$$
$$\vec{C} = 2 * \vec{r}$$

According to the formula max 2 − 2t/tmax, where tmax is the maximum number of iterations, the vector a will progressively shrink from 2 to 0. A random vector with values between 0 and 1 is represented by the symbol r. The A is constrained inside the interval [−a, a] by the injected random vector r. Notably, the whales are helped by the random vectors A and C to update their locations in order to reach the best solution. Bubble nets are used by humpback whales to catch and hold prey close to the water's surface. The spiral bubble net assault method may be represented mathematically as follows:

5. Results and Discussion

This section describes how to schedule results for various job amounts spread over many virtual machines. The modified EPSOA proposed in this study is compared to traditional PSO, Harris Hawks Optimizer (HHO), Genetic Algorithm (GA), and Ant Colony Optimization [16] (ACO) using a range of performance metrics, including as resource utilization, energy consumption, and execution cost. The simulations were conducted on a laptop running Windows 8 64-bit with 8 GB of RAM. CloudSim 3.0.3, a well-known program for modeling cloud systems, was used to carry out these simulations. The specifications for the hosts and data centers used in the simulation are listed in Table 1. Details on the features of the virtual machines (VMs) employed in the experiment are given in Table 2. Furthermore, the price structure for different Azure Bs-series is shown in Table 1, which is relevant for simulation cost considerations. The simulated workload used to evaluate the effectiveness of the suggested EPSOA algorithmm. A uniform distribution is used to create this artificial workload, guaranteeing that jobs of different sizes are distributed evenly. The High Performance Computing Centre (HPC2N) workload, a widely accepted benchmark for assessing the performance of distributed systems, serves as the focal point of the assessment. Task sizes and other crucial metrics for assessing the PSO algorithm's efficacy are among the realistic scenario data provided in the table. The resource use results for many algorithms, including EPSOA, PSO, ACO, HHO, and GA, using HPC2N workloads are shown in Figures 2 and 3. 40 or 80 virtual machines (VMs) were used in the studies, and the job quantity ranged from 250 to 2000. The results demonstrate that EPSOA uses resources more efficiently than other algorithms. The reason for this superiority in resource utilization is that EPSOA takes resource use into account when scheduling tasks for the right virtual machines (VMs), which leads to the effective use of VMs. Consequently, by optimizing resource utilization, EPSOA considerably improves overall performance, demonstrating its efficacy in inefficient task scheduling and RA when compared to PSO, ACO, HHO, and GA. Table 1 shows Prices for VM Table 2 shows Task Properties. [11-15]

Table 1 Prices for VM

Cores	Storage	Memory	Prices($)
3	32	16	0.05
6	64	32	0.17
9	96	48	0.32
12	128	64	0.48
15	160	80	0.63
18	192	96	0.82

Table 2 Task Properties

Tasks	Length of Task	Properties
300-2000	11000-85000	independent

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

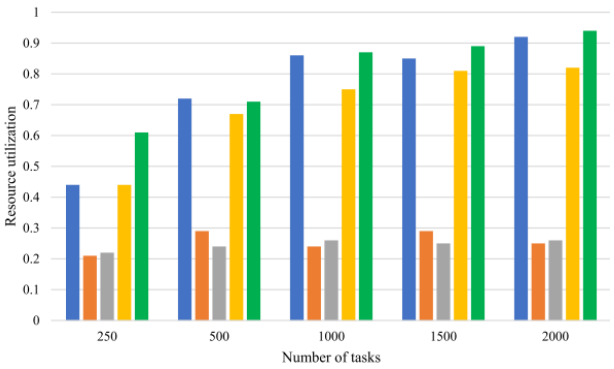

Figure 2 Utilization of Resources for a 40-VM HPC2N Workload

Figures 2, 3, and 4 compare the algorithms according to how much energy they use. This metric is essential for minimizing scheduling costs and durations because of the connection between scheduling energy, cost, and length. It is evident that the energy consumption of the PSO, ACO, GA, and HHO algorithms increases linearly with the number of jobs. However, EPSOA exhibits a slower growth in energy consumption, indicating that it is successful in regulating energy use even when the number of activities rises. EPSOA's effectiveness is further enhanced by its task count flexibility, which distinguishes it from other approaches that disregard changes in RA workload. EPSOA effectively assigns costlier and time-consuming tasks to virtual machines with more capacity by using this capability. Thus, it can be concluded that EPSOA excels in RA and task assignment, which facilitates the efficient usage of higher-capacity virtual machines (VMs) [17].

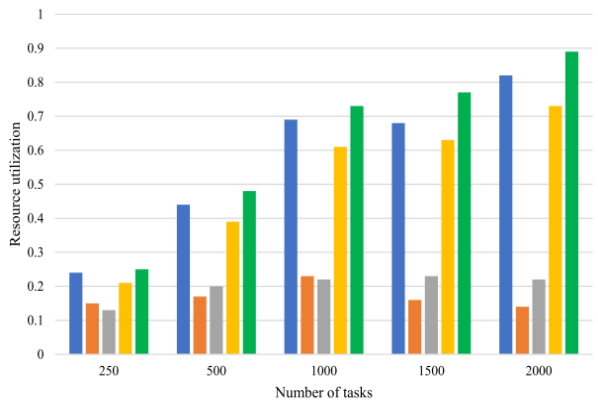

Figure 3 Utilization of Resources for an 80-VM HPC2N Workload

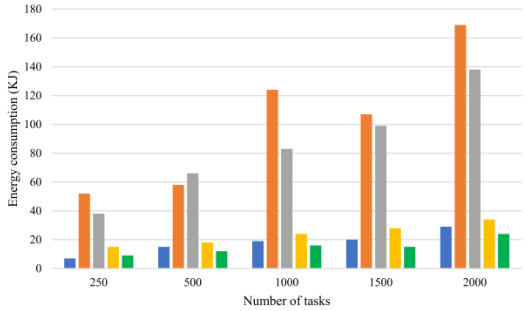

Figure 4 Energy Usage for 40 Virtual Machines in an HPC2N Application

Figures 2, 3, and 4 compare the execution cost of algorithms for simulated workloads and HPC2N. Execution costs may be influenced by factors such as task time and virtual machine type. Figures 4 and 5 demonstrate that EPSOA performs better than the conventional PSO approach in simulated and HPC2N workloads across a variety of task counts. For real activities ranging in size from 250 to 2000, EPSOA exhibits an average execution cost decrease of 9% to 41% in comparison to PSO. Similarly, for the simulated workload and task counts between 500 and 2000, the average drop compared to PSO ranges from 7 to 57%. Thus, as shown by the previously given figures, EPSOA regularly meets the goal of cost reduction in a variety of situations in addition to lowering execution costs.

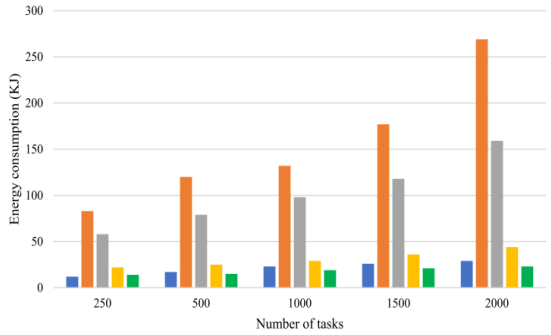

Figure 5 Energy Use for an 80-VM HPC2N Workload

Additionally, a non-parametric statistical technique for comparing two related samples is Wilcoxon's signed-rank test. This test is meant to evaluate how well the proposed EPSOA algorithm performs in comparison to other scheduling methods. that are already in use,

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

including PSO, ACO, GA, and HHO, in the context of CC resource scheduling. The test specifically looks at how EPSOA and the other algorithms vary in terms of energy use and execution costs under various workload circumstances. For each workload scenario,

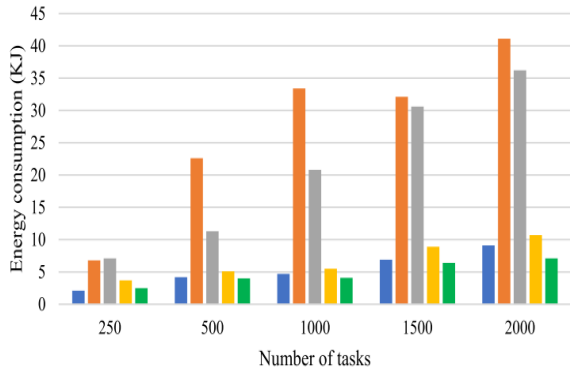

Figure 6 Energy Use for a 120-VM Simulated Workload

The energy consumption and execution costs resulting from running the EPSOA and comparison algorithms are paired. The associated pairs' differences are computed and ordered based on their absolute values. Wilcoxon's signed-rank test is then used to evaluate if performance has improved or declined statistically significantly, which determines if these changes substantially vary from zero. The research guarantees a thorough statistical analysis that takes into consideration the comparisons' paired nature and the data's non-normal distribution often seen in CC contexts by using Wilcoxon's signed-rank test. This method offers solid proof of the applicability and dependability of the suggested EPSOA performance improvements of the algorithm in terms of cost and energy efficiency under various workload conditions. Additionally, an ablation research was carried out in this work to carefully examine the distinct contributions of every element included into the adaptive crossover technique of the Improved Paticle Swarm Search Optimisation (IPSOA) algorithm, the Lévy fight mechanism, and other improvements. This method offers crucial insights into the efficacy and importance of these improvements by methodically separating and assessing the influence of each element on the overall performance of the program. This degree of information enables a more comprehensive understanding of how each element influences the algorithm's performance metrics, such as robustness to parameter perturbations, convergence speed, and solution quality. As a consequence, the findings of this ablation study provide helpful guidance for future researchers who want to apply these developments to their own proposed methodologies. Researchers may decide which improvements to prioritise or modify depending on the particular needs and features of their optimisation challenges by clearly defining the relative relevance of each component. In the end, this method makes it easier to create more specialised and effective optimisation algorithms, which propels progress in a number of domains where optimisation is essential. When compared to current algorithms like PSO, ACO, GA, and HHO, EPSOA achieves significant and diverse performance gains. First off, EPSOA is more efficient when it comes to energy usage, especially when the quantity of assignments increases. EPSOA's energy consumption rises more slowly than that of other algorithms, which exhibit a linear increase with the number of jobs. This shows that even with increased job demands, it is successful in controlling energy use. EPSOA's flexibility to adjust to different task counts, which other methods lack, enables it to distribute work to virtual machines (VMs) with higher capacity in an effective manner, reducing energy use. As a result of EPSOA's superior performance in task assignment and RA, bigger capacity virtual machines are used effectively. Additionally, in terms of execution costs, EPSOA performs better than the traditional PSO algorithm on simulated and HPC2N workloads, reliably reducing execution costs in a variety of circumstances. When compared to PSO, EPSOA typically reduces execution costs by 9 to 57% for real activities with a task count between 350 and 3000 and synthetic workloads with a task count between 600 and 3000. This illustrates not only how well EPSOA reduces execution costs but also how consistently it meets cost-cutting objectives in a range of workload conditions. Thus, the efficiency of EPSOA in optimizing task assignment, RA, and overall scheduling efficiency in CC contexts is shown by the

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

performance gains it achieves, which are demonstrated by lower energy consumption and execution costs when compared to other algorithms like PSO. [16-17]

Conclusion

Effective work management in CC systems requires multi-objective and efficient scheduling strategies due to the constantly increasing demand for cloud services. The EPSOA was presented in this study as an innovative solution to the challenges of multi-objective task scheduling in the cloud. EPSOA showed encouraging results in optimizing cloud work scheduling issues by including the Lévy battle tactic into the PSO. EPSOA proposed better performance in various test scenarios simulated using the Cloudsim tool by enlarging the search space with Lévy battle. The usefulness of EPSOA in attaining improved resource utilisation, decreased energy consumption, and minimised execution costs was shown by its comparison versus current algorithms. These results demonstrated how well EPSOA can handle the complex problems associated with multi-objective cloud job scheduling. The results of this study provide a thorough, effective, and creative method for multi-objective task scheduling, which greatly advances the subject of CC. With its ability to optimise resource management in cloud systems while taking into account many competing goals, Te EPSOA shows potential for practical applications. Even though EPSOA shows significant progress in multi-objective task scheduling, there is still room for improvement and investigation. Furthermore, a number of issues might restrict the study's management implications of defect detection. First off, even though defect detection techniques may improve system performance and dependability, putting them into practice often entails extra expenses and RA. The cost-benefit analysis of implementing and maintaining defect detection systems must thus be taken into account, particularly for smaller or more financially strapped organizations. Additionally, the intricacy and unpredictability of cloud configurations, together with the specific types of flaws experienced, may affect how successful fault detection techniques are. Therefore, it might be difficult to extrapolate managerial consequences across various cloud systems and sectors. To overcome these constraints and improve the management consequences of defect detection in CC, future research might go in a number of different areas. First off, decision-makers would benefit greatly from examining the trade-offs between the potential savings via improved system reliability and reduced downtime and the costs of trouble detection systems. Future research may also focus on fine-tuning the algorithm's parameters, scaling it for larger and more complex cloud environments, and analyzing how well it adjusts to dynamic and real-time scenarios.

References

[1]. Pourghebleh B *et al.* (2021), "The importance of nature-inspired meta-heuristic algorithms for solving virtual machine consolidation problem in cloud environments", Cluster Computing, 24(3):1–24, https:// link.springer. com/article/ 10.1007/s10586-021-03294-4.

[2]. Hayyolalam V et al, "Exploring the state-of-the-art service composition approaches in cloud manufacturing systems to enhance upcoming techniques", IJAMT, 105(1), https://link.springer.com/article/10.1007%2Fs0 0170-019-04213-z.

[3]. Hayyolalam V et al, "Single-objective service composition methods in cloud manufacturing systems: Recent techniques, classifcation, and future trends", Concurrent Computation Practice and Experience, 34(5):6698, http://dx.doi.org/10.1002/cpe.6698.

[4]. P, Patel S, Singh P (2022), "5G Enabled Smart City Using Cloud Environment", In book Predictive Analytics in Cloud, Fog, and Edge Computing: Perspectives and Practices of Blockchain, IoT, and 5G. Springer, Germany, p 199–226, http://dx.doi.org/10.1007/978-3-031-18034-7_12.

[5]. Hanini M et al, "Dynamic VM allocation and trafc control to manage QoS and energy consumption in cloud computing environment", IJCAT, 60(4):307–316, http://dx.doi.org/10.1504/IJCAT.2019.101168.

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 03 Issue: 02 February 2025
Page No: 129-137
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2025.0017

[6]. Nabi S, Ahmad M, Ibrahim M, Hamam H (2022), "AdPSO: adaptive PSO-based task scheduling approach for cloud computing", Sensors 22(3):920.
[7]. Yu Y, Su Y (2019), "Cloud task scheduling algorithm based on three queues and dynamic priority", In 2019 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS), IEEE, United States of America, p 278–282.
[8]. Minarolli D (2022), "A Distributed Task Scheduling Approach for Cloud Computing Based on Ant Colony Optimization and Queue Load Information", International Conference on P2P, Parallel, Grid, Cloud and Internet Computing. Springer, pp 13–24.
[9]. Zhang Z, Zhao M, Wang H, Cui Z, Zhang W (2022), "An efcient interval many-objective evolutionary algorithm for cloud task scheduling problem under uncertainty", Inf Sci, 583:56–72.
[10]. Alsaidy SA, Abbood AD, Sahib MA (2022), "Heuristic initialization of PSO task scheduling algorithm in cloud computing.",J King Saud Univ-Comp Inform Sci, 34(6):2370–2382.
[11]. Dubey K, Sharma SC (2021), "A novel multi-objective CR-PSO task scheduling algorithm with deadline constraint in cloud Computing", Sustain Comput Inform Syst,32:100605.
[12]. Emami H (2022), "Cloud task scheduling using enhanced sunfower optimization algorithm", ICT Express, 8(1):97–100.
[13]. Gong R, Li D, Hong L, Xie N (2024), "Task scheduling in cloud computing environment based on enhanced marine predator algorithm", Cluster Comput ,27(1):1–15.
[14]. Hu Q, Wu X, Dong S (2023), "A two-stage multi-objective task scheduling framework based on invasive tumor growth optimization algorithm for cloud computing", J Grid Comput, 21(2):31.
[15]. Mirjalili S, Lewis A (2016),"The whale optimization algorithm", Adv Eng Softw, 95:51–67.
[16]. Zeenath Sultana, Dr.Raafiya Gulmeher and Asra Sarwath, "Methods for optimizing the assignment of cloud computing resources and the scheduling of related tasks", IJEECS, Vol 33,No 2, Feb 2024. http://dx.doi.org/10.11591/ijeecs.v33.i2.pp1092-1099.
[17]. Asra Sarwath, Dr.Raafiya Gulmeher and Zeenath Sultana, "Spark Mllib intrusion detection mechanism using machine learning models", IJEECS, Vol 33,No 2, Feb 2024, http:// dx.doi.org/ 10.11591/ ijeecs.v33.i2.pp1235-1242.