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DEGREE OF IMBALANCE FOR TASK SCHEDULING IN CLOUD COMPUTING

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ABSTRACT

The increasing reliance on cloud computing platforms for data-intensive applications has made efficient task scheduling a critical factor for maximizing resource utilization and minimizing the degree of imbalance. Inefficient task scheduling in these complex, distributed environments can lead to significant performance bottlenecks, including workload imbalance, which negatively impacts overall system efficiency and scalability. Task scheduling in cloud environments is a well-known NP-complete problem, further compounding the challenge of achieving optimal solutions. While existing metaheuristic approaches offer some mitigation, they often struggle to effectively balance exploration and exploitation, leading to suboptimal solutions and slow convergence.

This study addresses this critical need by refining the previously proposed Henry Gas-Harris Hawks Modified Opposition (HGHHM) algorithm to explicitly minimize the degree of imbalance in task scheduling. We introduce a novel integration of Henry Gas Solubility Optimization (HGSO) and Harris Hawks Optimization (HHO) enhanced with a Modified Comprehensive Opposition-Based Learning (MOBL) strategy. This unique combination allows HGHHM to effectively explore the solution space while exploiting promising regions, leading to a more balanced workload distribution. Simulations using the CloudSim toolkit demonstrate that the improved HGHHM algorithm significantly reduces the degree of imbalance compared to the Cuckoo-based Discrete Symbiotic Organism Search (CDSOS) technique, achieving superior performance in terms of convergence speed and solution quality while avoiding local optima. A t-test confirms the statistical significance of these improvements, highlighting the potential of hybrid metaheuristic methods for optimizing task scheduling in large-scale cloud computing environments.

Keywords: *HGHHM; Cloud computing; Meta-heuristic; Scheduling; Optimization; Degree of imbalance.*

1. INTRODUCTION

The widespread adoption of the internet has driven significant advancements in data processing and storage, culminating in the emergence of cloud computing [1, 2]. One of the primary challenges in cloud computing is efficiently and reliably scheduling jobs to available resources. Cloud computing necessitates the capacity to effectively handle numerous concurrent users while ensuring high quality of service (QoS) for all customers. Inefficient task scheduling can lead to significant performance bottlenecks, including underutilization of resources, increased job completion times, and, critically, workload imbalance, which negatively impacts overall system throughput and scalability [5, 6].

Cloud computing environments utilize virtual machines (VMs) with diverse processing capabilities and features. To minimize workload imbalance, effective load balancing strategies are crucial during task scheduling. This requires careful coordination and optimization to ensure efficient distribution of tasks across VMs [11-13]. Task scheduling algorithms aim to effectively distribute the system's workload while considering the overall execution

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time of available virtual machines. Various studies have explored different approaches, including traditional, heuristic, metaheuristic, to address the challenge of creating efficient task scheduling sequences in cloud computing environments [7, 8].

While traditional and heuristic techniques offer valuable solutions for job scheduling, they often struggle to guarantee optimal solutions, especially in large-scale and dynamic environments. In contrast, metaheuristic algorithms have demonstrated superior performance in tackling complex optimization problems, including task scheduling. These algorithms can often find near-optimal solutions in polynomial time rather than exponential time [9, 10], making them well-suited for addressing the challenges of cloud computing. Building upon our previous work [30], which focused on improving makespan and resource utilization, this study extends the HGHHM algorithm by incorporating the degree of imbalance as a new optimization objective

The primary goal of this study is to minimize the degree of imbalance in cloud task scheduling, thereby enhancing overall system performance and QoS. To achieve this, the proposed method focuses on improving convergence rates and balancing exploration and exploitation. The result is improved job distribution across virtual machines and reduced overall imbalance. Through extensive simulations using the CloudSim toolkit, we demonstrate that the improved HGHHM algorithm effectively reduces workload imbalance while optimizing key performance metrics such as resource utilization and job completion time. This research contributes to the growing body of work on metaheuristic-based scheduling algorithms, offering a robust solution to one of the most persistent challenges in cloud computing.

The main contributions of the paper are:

i. An objective function for optimum task scheduling on VMs is described, taking into account the VM utilization level in order to reduce the degree of imbalance within the search space.
ii. Hybridization of HGSO with HHO and MOBL to discover the best solution in the global solution regions defined by HGSO.
iii. Implementation of the proposed approach in CloudSim.
iv. A comparison between CDSOS and the proposed technique in terms of degree of imbalance.
v. An empirical analysis of convergence speed using HGHHM and CDSOS.

The remainder of this paper is organized as follows: Section 2 reviews related work, providing an overview of key studies in the field. Section 3 discusses how the scheduling problem is framed as an optimization challenge. Section 4 present the experimental environment Experimental results and their analysis are presented in Section 5. The limitation and future work presented in section 6. Section 7 presents the threat of validity. Finally, Section 8 concludes the paper, offering insights and potential directions for future research in this area.

2. RELATED WORKS

Existing task scheduling approaches in cloud computing face several limitations. While cloud computing has advanced significantly, effectively allocating resources and scheduling workloads remain challenging. Many current approaches struggle to adapt to the dynamic nature of modern computing environments, often failing to address issues such as a high degree of imbalance. Managing concurrent users and meeting diverse Quality of Service (QoS) requirements further complicates the task scheduling problem. These limitations necessitate innovative solutions to improve the efficiency of cloud systems. This study focuses on enhancing task scheduling by addressing the issue of imbalance, which can be mitigated by improving exploration and exploitation capabilities to avoid local optima [11, 12]

In this overview, we first examined many techniques that seek to balance exploration and exploitation tactics in order to maximize efficiency and minimize degree of imbalance. For example, (Kruekaew & Kimpan, 2020) [32] this research introduces the HABC algorithm, an approach for optimizing task scheduling and load balancing in cloud computing environments, encompassing both homogeneous and heterogeneous systems. The HABC algorithm was evaluated through simulations to assess its effectiveness in optimizing task scheduling and load balancing for various workloads. Performance comparisons were conducted against ACO algorithms, PSO algorithms, and improved PSO algorithms. However, the initial study relied on simulations with limited datasets, potentially limiting its generalizability to real-world scenarios with increasing demands.

To further enhance load balancing in cloud environments, Velliangiri et al. [19] proposed a Hybrid Electro Search with Genetic Algorithm. This algorithm considers multiple factors, including makespan, load balancing, resource consumption, and multi-cloud costs.

As similar, the study introduced by Alboaneen et al., proposed method aims to schedule tasks to virtual machines while minimizing execution cost and optimizing load balancing. By comparing

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different scheduling scenarios, the study demonstrates the effectiveness of the proposed approach in maximizing resource utilization and minimizing execution cost, makespan, and degree of imbalance [31]

3. PROBLEM FORMULATION

The task scheduling problem is structured to correspond with the objective function, guaranteeing that each work assign alternative is equitably assessed against the overall criteria. The objective function is crucial in this procedure, facilitating a polynomial-time approximation within the HGHHM algorithm. The major objective is to yield outcomes that closely resemble the optimal solution, particularly by evaluating the effectiveness of this method in reducing the level of imbalance. Scheduling aims to allocate tasks effectively among virtual machines (VMs) to mitigate imbalance. This purpose is fundamental to task scheduling. Examine a collection of autonomous activities that require scheduling for execution on a diverse array of virtual machines. The collection of VMs is represented as $VM = \{VMj \mid m \geq j \geq 1\}$, with m indicating the total quantity of VMs. The defined task set is denoted as $Tk = \{TKi \mid n \geq i \geq 1\}$, where n signifies the total quantity of tasks. The objective is to reduce the degree of imbalance by efficiently allocating each task TKi ∀ $i = \{1,2, \ldots, n\}$ to a corresponding virtual machine VMj ∀ j = $\{1,2, \ldots, m\}$. Equation 1 is utilized to determine the execution duration of task TKi on virtual machine VMj [29, 30].

$$\text{Exe j} = \sum xij * \frac{TKij}{nPRj} \text{ X } VMmipj \quad \ldots\ldots. (1)$$

Where TKij represents the workload assigned to VMj; VMmipj denotes the duration of a task in Million Instructions (MIs); VMmipj signifies the processing speed of VMj in Millions Instructions per Second (MIPS); and nPRj indicates the quantity of processing elements. The execution duration of the task assigned to VMj is denoted by exej; if task i is assigned to virtual machine j, then xij is equal to 1. If the task is executed by several virtual machines VMj for all j = 1, 2, …, m

Equation 2 is employed to calculate the total execution time of the job managed over all virtual machines VMj, where TKi for all i = 1, 2, …, n.

$$\text{T}exek = \sum exek \quad \ldots\ldots. (2)$$

$\forall i = \{1,2, \ldots, n\}$ j $= \{1,2, \ldots, m\}$

As a result, Equation 3 shows the problem's objective function, which is to reduce the degree of imbalance (DI).

$$DI = T_{max} - T_{min} \ / \ T_{avg} \quad \ldots\ldots. (3)$$

Where T_{max} , T_{min} , and T_{avg}, which represent the highest, minimum, and average total execution times over all resources. Derived from the model presented by [27], the DI equation is a useful tool for assessing the efficacy of any task scheduling solution that has been created. It enables us to evaluate the effectiveness of such a solution in addressing actual NP-hard scheduling problems. Moreover, this model may be easily integrated into a meta-heuristic algorithm inspired by nature to speed up the search for the best solutions.

4. EXPERIMENTAL ENVIRONMENT

This section details the experimental environment, including the datasets and parameters used for evaluating HGHHM algorithm. The performance of HGHHM for degree of imbalance was assessed using the CloudSim simulator, a high-performance open-source framework for modeling and simulating cloud computing environments [78]. CloudSim provides support for modeling key cloud system components, such as data centers, hosts, virtual machines (VMs), cloud service brokers, and resource provisioning strategies. The experiments were conducted on a desktop computer equipped with an Intel Core i5-2430M CPU @ 2.40 GHz, 4 GB RAM, and utilizing CloudSim toolkit version 3.0.3. Table 1 presents the detailed configuration of the simulation environment. All experiments involved 25 VMs hosted on two host machines within a single data center. The processing capacity of VMs was measured in MIPS.

Table 1. Configurations of experimental parameters

Cloud entity	Variable	Value
Datacenter		2
Host		2
	Storage	1 T
	RAM	16 GB
	Bandwidth	10 Gb/s
VM	No. of VMs	25
	MIPS	5000
	Size	10 GB
	RAM	0.5 GB

Furthermore, a synthesized dataset was used in the test experiments to evaluate degree of imbalance of

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the HGHHM algorithm its setting showed in table 2. These were considered to be non-preemptive and independent jobs. In this investigation, the workload traces from several distributions (normal, uniform, left, and right) were used [15]. The accuracy of outcome predictions was increased by independently completing about 1000 cycles for each technique in each trial. The results were then averaged over the course of several iterations [15, 17].

Table 2. Synthetic workload settings

Parameters	Value
No. of cloudlets (jobs)	100 to 1000
Length	1000 to 20000 MI

5. RESULTS AND DISCUSSION

This approach emphasizes how important it is to achieve different levels of imbalance. The maximum, minimum, and average values are defined by the simulation results. The comparison with CDSOS focuses on assessing the degree of imbalance. Figures 1-4 offer a comprehensive comparison of the results between the two algorithms, highlighting how HGHHM outperforms the compared algorithm in terms of the degree of imbalance. These figures illustrate the superior capability of HGHHM in achieving a more balanced distribution of tasks across resources, thereby improving overall scheduling efficiency. The visual representation underscores the effectiveness of the HGHHM in reducing imbalance, which is crucial for enhancing cloud system performance. In addition, Tables 3-6 provide detailed simulation outcomes, showcasing various performance metrics across different test cases. These tables offer insights into how HGHHM consistently delivers better results across multiple dimensions, including resource utilization and task distribution. Table 7 presents the percentage improvements in the degree of imbalance (DI), providing a clear summary of the simulation results. These findings demonstrate that the HGHHM algorithm achieves near-optimal performance and significantly outperforms the benchmark scheduling algorithms.

The results highlight HGHHM's effectiveness in minimizing imbalances, further confirming its superiority in optimizing task scheduling in cloud environments. We observed a significant reduction in workload imbalance, which was our primary objective. To quantify this, we used the 'degree of imbalance' metric, which directly measures the uneven distribution of tasks across VMs. Table 8, in particular, presents the statistical validation of the results, where the p-value is shown to be less than 0.05. This indicates that the null hypothesis, which assumes no significant difference between the performances of the two algorithms, is rejected. The rejection of the null hypothesis confirms that the observed improvements in the degree of imbalance by HGHHM are statistically significant, further validating the robustness of the proposed approach.

Moreover, a lower DI value indicates that HGHHM outperforms the comparative CDSOS algorithm by achieving better task balance. The Harris Hawks algorithm strengthens HGHHM's local search process, enabling efficient load balancing and more effective distribution decisions with minimal resource waste. Figures representing task instances from 100 to 1000 demonstrate the performance improvements based on DI. This approach efficiently assigns jobs to virtual machines with the highest computational demands, ensuring optimal resource allocation. As a result, the method achieved higher convergence rates and a better balance between exploration and exploitation, leading to improved job distribution across virtual machines and reduced overall imbalance.

6. LIMITATIONS AND FUTURE WORK

This study focused on minimizing imbalance as the primary objective. Other important QoS parameters, such as cost, energy consumption, and security, were not explicitly considered. Future research should investigate the multi-objective optimization of task scheduling, incorporating these additional factors. Moreover, the CloudSim simulator provides a valuable platform for evaluating scheduling algorithms. However, it simplifies certain aspects of real-world cloud environments. Therefore, deploying and evaluating HGHHM in a real cloud environment would provide more realistic performance data and identify potential challenges related to its practical implementation. Future work will involve testing the algorithm in a live cloud environment to validate the simulation results and assess its performance under real-world conditions.

7. THREAT OF VALIDITY

Despite our efforts to conduct a comprehensive study, certain threats to its validity may persist. Therefore, readers are advised to consider these limitations when evaluating or utilizing the results and conclusions presented in this work:

i. Internal Validity

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Implementation Errors: There's always a possibility of bugs or errors in the implementation of the algorithm or the simulation setup. Thorough testing and validation are crucial to minimize this threat.

ii. External Validity

The HPC2N and NASA datasets, while commonly used, might not fully represent the diversity of real-world workloads.

8. CONCLUSION

Cloud computing faces the challenge of efficiently scheduling jobs across virtual machines. Task scheduling in this context is an NP-hard problem, where inefficient distribution can lead to increased imbalance and negatively impact overall system performance. Building upon previous work, this study introduces a novel approach by incorporating the degree of imbalance as a key objective within the existing HGHHM framework. The results demonstrate that HGHHM effectively addresses this challenge by reducing the degree of imbalance during task scheduling. By leveraging a hybrid approach, HGHHM enhances exploration and exploitation capabilities, enabling it to discover better solutions and achieve more balanced task allocation across virtual machines. This leads to optimized resource utilization and minimizes performance bottlenecks caused by imbalanced workloads. Simulations conducted using the CloudSim simulator show that HGHHM outperforms the CDSOS task scheduling algorithm, particularly in terms of reducing imbalance across a range of task instances. Statistical analysis, with p-values less than 0.05, further confirms the statistical significance of these results, highlighting HGHHM's superior ability to enhance cloud system performance.

This work contributes significantly to the field of cloud computing by proposing a robust and effective solution to the challenging task scheduling problem.

In conclusion, this work offers a novel and effective approach to the challenging task scheduling problem in cloud computing. While further research is needed to address the limitations identified, we believe that HGHHM represents a significant step towards achieving more balanced and efficient resource allocation in cloud environments.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table 3: Comparison Of The Imbalance Degree Attained By The CDSOS And HGHHM Algorithms For The Right-Skewed Distribution Dataset.

	CDSOS			HGHHM		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
100	15.75	19.91	17.75	4.01	18.62	15.55
200	15.62	19.91	18.44	12.63	18.24	15.68
300	17.15	19.91	18.69	13.17	17.80	15.91
400	16.51	19.91	19.04	9.55	14.04	12.47
500	16.22	19.91	19.19	12.42	15.29	13.54
600	17.88	19.91	19.14	8.88	13.97	11.06
700	18.37	19.91	19.37	9.28	12.87	10.80
800	18.52	19.91	19.36	8.83	14.26	10.82
900	18.5	19.91	19.38	8.76	14.26	11.24
1000	18.67	19.91	19.57	8.57	13.67	10.94

Table 4: Comparison Of The Imbalance Degree Attained By The CDSOS And HGHHM Algorithms For The Left-Skewed Distribution Dataset.

	CDSOS			HGHHM		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
100	16.5	19.91	17.98	11.71	16.30	13.35
200	17.49	19.91	18.66	10.96	15.81	13.43
300	16.99	19.91	18.75	9.54	12.95	11.68
400	16.66	19.91	18.75	16.33	16.33	12.11
500	17.1	19.91	19.15	6.87	12.75	10.04
600	18.74	19.91	19.35	6.50	13.09	10.02
700	18	19.91	19.41	7.50	10.66	9.34
800	18.43	19.91	19.36	6.46	10.68	8.98
900	18.43	19.91	19.41	7.06	11.64	8.43
1000	18.34	19.91	19.53	5.66	10.79	8.20

Table 5: Comparison Of The Imbalance Degree Attained By The CDSOS And HGHHM Algorithms For The Uniform Distribution Dataset.

	CDSOS			HGHHM		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
100	16.57	19.91	17.83	13.25	18.54	15.77
200	17.33	19.91	18.62	10.93	19.20	15.83
300	17.62	19.91	18.71	9.97	16.00	13.78
400	17.85	19.91	18.91	11.00	16.48	13.26
500	18.28	19.91	19.2	9.08	15.48	12.11
600	17.74	19.91	19.19	9.65	15.96	12.02
700	16.8	19.91	19.22	10.23	14.46	11.65
800	18.21	19.91	19.32	8.74	11.86	10.60
900	18.31	19.91	19.29	8.73	11.26	10.13
1000	18.46	19.91	19.46	7.20	10.00	9.29

Table 6: Comparison Of The Imbalance Degree Attained By The CDSOS And HGHHM Algorithms For The Normal Distribution Dataset.

	CDSOS			HGHHM		
	Min	**Max**	**Avg.**	**Min**	**Max**	**Avg.**
100	15.77	18.59	17.63	12.48	18.50	15.65
200	17.32	19.44	18.54	11.28	16.85	13.84
300	16.24	19.44	18.49	9.48	16.05	9.48
400	17.02	19.65	18.8	9.86	14.31	11.58
500	18.04	19.67	19.13	8.63	12.71	10.56
600	17.86	19.75	19.23	3.55	12.87	9.75
700	18.8	19.8	19.37	7.55	14.49	9.92
800	18.77	19.91	19.46	7.84	11.96	9.76
900	18.4	19.91	19.45	7.20	11.03	9.01
1000	18.33	19.91	19.53	8.43	10.65	9.57

Table 7: Variation Of PIR% Based On DI

DATASETS	Total average DI (sec) CDSOS	Total average DI (sec) HGHHM	PIR%
Normal distribution	17.66	8.63	51.12
Left-half distribution	17.67	8.86	49.86
Right-half distribution	17.32	9.61	44.52
Uniform distribution	17.72	9.88	44.24

Table 8: Comprehensive Results Of The Wilcoxon Signed Test For MKS

Detail	P- Value
At $p < .05$, the outcome is significant. The null hypothesis is rejected and there is a significant difference between the groups if the p-value is less than 0.05. The null hypothesis fails to reject if the p-value is greater than 0.05, indicating that there is no discernible difference between the groups. Our null hypothesis, H_0, is thus rejected	0.01

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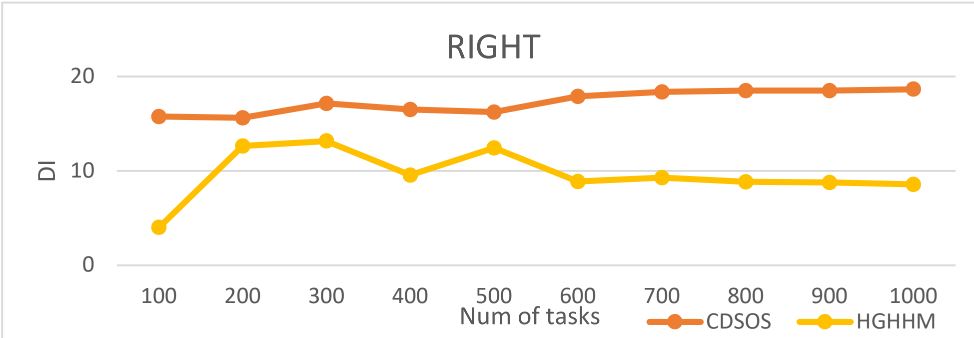

Figure 1: Degree Of Imbalance For Right Half Distribution

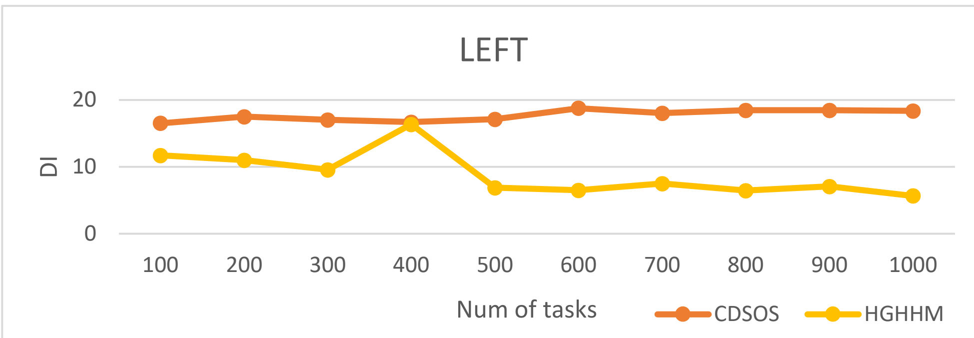

Figure 2: Degree of Imbalance for Left Half Distribution Dataset

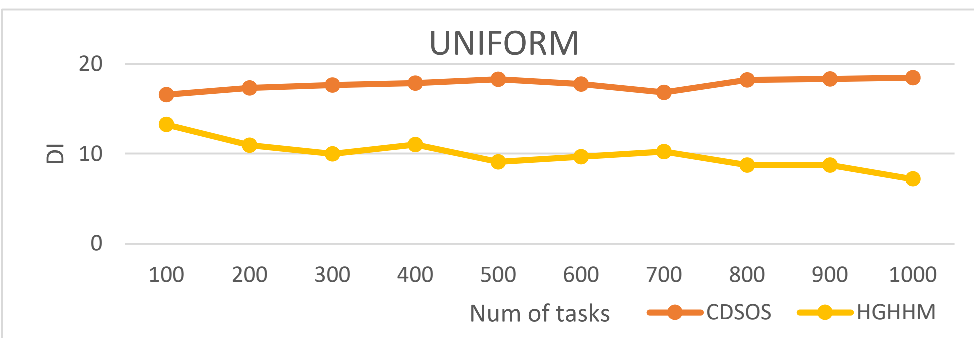

Figure 3: Degree of Imbalance for Uniform Distribution Dataset

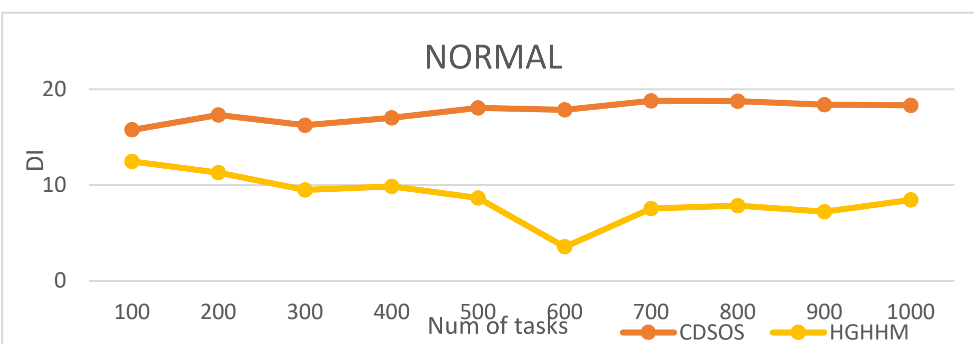

Figure 4: Degree of Imbalance for Normal Distribution Dataset