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Hybridized Darts Game with Beluga Whale Optimization Strategy for Efficient Task Scheduling with Optimal Load Balancing in Cloud Computing

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Abstract-A cloud computing technology permits clients to use hardware and software technology virtually on a subscription basis. The task scheduling process is planned to effectively minimize implementation time and cost while simultaneously increasing resource utilization, and it is one of the most common problems in cloud computing systems. The Nondeterministic Polynomial (NP)-hard optimization problem occurs due to limitations like an insufficient make-span, excessive resource utilization, low implementation costs, and immediate response for scheduling. The task allocation is NP-hard because of the increase in the amount of combinations and computing resources. In this work, a hybrid heuristic optimization technique with load balancing is implemented for optimal task scheduling to increase the performance of service providers in the cloud infrastructure. Thus, the issues that occur in the scheduling process is greatly reduced. The load balancing problem is effectively solved with the help of the proposed task scheduling scheme. The allocation of tasks to the machines based on the workload is done with the help of the proposed Hybridized Darts Game-Based Beluga Whale Optimization Algorithm (HDG-BWOA). The objective functions like higher Cloud Data Center (CDC) resource consumption, increased task assurance ratio, minimized mean reaction time, and reduced energy utilization are considered while allocating the tasks to the virtual machines. This task scheduling approach ensures flexibility among virtual machines, preventing them from overloading or underloading. Also, using this technique, more tasks is efficiently completed within the deadline. The efficacy of the offered arrangement is ensured with the conventional heuristic-based task scheduling approaches in accordance with various evaluation measures.

Keywords-Task Scheduling; Optimal Load Balancing; Cloud Computing; Hybridized Darts Game-Based Beluga Whale Optimization Algorithm; Objective Functions

I. INTRODUCTION

Cloud computing has emerged in recent days, and it is working with current internet technologies. Traditional cloud computing resembles service-oriented computing more because it provides applications, platforms, and infrastructure via the Internet based on a pay-per-use business approach [9]. "High-Performance Computing (HPC)" resources, along with other IT tools, are merged as a single "Cloud Data Centre (CDC)", in which HPC resources are prepared to fulfill customer needs [10]. The complexity involved in hosts and equipment also results in high energy expenditures, and this process also has an impact on the environment [11]. In recent years, a wide range of businesses, organizations, and academic institutions have selected CDCs to meet their technological and data storage demands [12]. The user can be relieved from the information technology infrastructure as a result of the cloud computing paradigm [13]. Technical resources within the CDC often consist of numerous cooling facilities and computers that are reliable, versatile, and cost-effective [14].

Cooperative computing is enabled by enormous data centers, enormous quantities of storage, high-bandwidth systems, and other shared computing resources [15]. As a result of this process, a large number of computers must be effectively managed in data centers, making cloud technology a superior computing model [16]. Consolidated computing, parallel processing, service computing, and grid technology are some of the stages in cloud computing [17]. In a recent research field, the task schedule in the data center is a critical process [18]. A successful task scheduling mechanism is crucial for balancing the load in the data centers. To reduce running time and increase the utilization of assets, task scheduling is considered an important task [19]. If tasks are not properly scheduled, concurrency cannot be completely realized. Inconvenient scheduling generates long implementation instances, high expenses, and inadequate resource utilization, which affects the overall performance of the cloud structure [20]. Better resource utilization is attained through the use of effective scheduling strategies. Scheduling approaches minimize expenses and execution time by assigning tasks to virtual nodes. The pay-per-use concept is used to operate the services given by cloud suppliers. The "Service Level Agreement (SLA)" establishes the "Quality Of Service (QoS)" provided to users [21]. The storage, bandwidth, and reaction time of each task are different. A task breaks the SLA if it doesn't have the necessary resources. The cloud provider's QoS is managed if the SLA violation of the data center is high [22].

The application of meta-heuristic algorithms and machine learning algorithms for task scheduling has recently caught the attention of researchers [23]. Multi-objective task scheduling difficulties are often solved with meta-heuristic strategies like "Genetic Algorithm (GA)", "Particle Swarm Optimization (PSO)", "Ant Colony Optimization (ACO)", and "Harmony Search (HS)". The processing overhead rises as a result of the long execution time of meta-heuristic algorithms [24]. The issues associated with these approaches are structured as follows: Initially, the execution time is increased, and it cannot handle the dynamic nature of cloud structures. In order to check the local and global optimal regions, meta-heuristic techniques are necessary [25]. If the algorithm finds the local optimal zone by accident, it traps it and moves quickly to the global optimal region. The conventional task scheduling approach takes more cost to program the tasks in a virtual machine of the cloud structure. Moreover, the traditional PSO-based task scheduling model does not achieve reliability during the task arrangement method. So, the researchers have suggested a novel hybrid meta-heuristic optimization approach is offered to address these difficulties.

The signification contributions of the hybrid optimization-based task scheduling process are detailed as follows.

- To develop the hybrid optimization-based task allocation model for allocating the tasks to the virtual machine of the cloud based on the capacity so that the task can be finalized in a short period without affecting the system performance.
- To offer the HDG-BWOA by integrating the DGO and BWO for optimizing the total amount of task that has to be arranged to the virtual machine of the cloud platform.
- To allocate the task to a proper virtual resource, an HDG-BWOA is recommended. It optimizes the task to be scheduled to the virtual resource for lowering the utilization of energy, mean reply time and resource employment and maximizing the task guarantee ratio during the task allocation process.
- The performance of the suggested hybrid optimization-based task scheduling model is analyzed by correlating the results of the explored model with the existing techniques in terms of various constraints.

The leftover parts of the HDG-BWOA-based task scheduling with optimal load balancing are described as follows. The existing task allocating model and its uses and limitations are structured in part II. In part III, the principle behind the task scheduling process with optimal load balancing in cloud computing is discussed. The development of hybridized darts game-based BWO as an efficient task scheduling algorithm is given in part IV. The objective function of task scheduling and the description of objective constraints are elucidated in part V. The output and conversation of the HDG-BWOA-based task scheduling with optimal load balancing are given in part VI. Finally, the part VII concludes this paper.

II. LITERATURE SURVEY

A. Related Works

In 2020, Sharma and Garg [1] have put forward a supervised neural network-based resource-efficient autonomous task scheduler with the goal of decreasing makespan, energy use, operation overhead, and the total number of active units. The suggested "Artificial Neural Network (ANN)-based scheduler" took an arriving task and the present state of the cloud environment as inputs. Here, the huge dataset was generated by the genetic algorithm. The developed model was compared with the genetic algorithm, "MinMIN-MINMin," and the "linear regression method-based energy efficient task schedulers" to determine the efficacy of the developed model in cloud environments. Findings demonstrated that the proposed work surpassed the existing algorithms.

In 2021, Marahatta *et al.* [2] have provided an "Efficient Dynamic Scheduling Strategy (EDS)" in a virtualized CDC. In accordance with a previous scheduling record, a variety of tasks and virtual machines in the scheduling scheme were initially identified. Then, similar-type tasks were grouped to get the operating status of the host. Based on finding results, EDS significantly surpassed the previous allocating methods in terms of resource utilization of CDC, consumption of energy mean reaction time, and task assurance ratio.

In 2022, Yuan *et al.* [3] have suggested a task scheduling strategy to reduce energy costs and the "Average Task Loss Probability (ATLP)" of clouds. Here, ATLP and the global mean were jointly optimized to minimize the energy cost of all clouds. The allocation of tasks to the web portal and the management of the CDC were considered as most important tasks. However, it was impossible to achieve joint optimization in a cloud environment in which variables such as electricity costs and server accessibility showed temporal changes. The QoS of tasks and minimization of mean energy expenditure were not effectively implemented in the present research due to their coarse-grained characteristics. A brand-new method called adaptive "simulated annealing-based bi-objective differential evolution" was offered for a real-time task scheduling approach that enhanced the power cost while maintaining the QoS. Investigations showed that the cost requirements of the proposed model for scheduling the task were lower than the existing techniques. It may also be used in smart cities, automated manufacturing etc.

In 2019, Lu and Sun [4] have suggested a unique energy-efficient load-balancing global optimization algorithm to address the issue of energy consumption in cloud computing. The developed model was also called the resource-aware load clonal method for task scheduling. Initially, the difficulty in the task scheduling process was conceived as a multimodal optimization issue that attempted to maximize both load distribution and consumption of energy. The suggested algorithm may efficiently minimize the usage of energy in a sustainable cloud era, and its investigating and exploiting abilities could be strengthened and well-stabilized.

In 2020, Sha and Santhosh [5] have offered a hybrid optimization-based task scheduling technique that effectively schedules the tasks with a minimum delay. In addition to these, the total production time, time required for execution, waiting period, effectiveness, and utilization were taken into consideration in the task scheduling process. Simulation findings showed that the recommended scheduling method surpassed the traditional scheduling method over various performance metrics.

In 2022, Kakkottakath *et al.* [6] have suggested a "Multi-Objective Hybrid PSO (MOHPSO)" to enhance the task scheduling process in internet-based computing. "Fuzzy Manhattan distance-based clustering" was employed to group the resources in the cloud. In order to enhance the investigation and searching abilities of the optimization algorithm and schedule the tasks in a cloud environment, the conventional "Search and Rescue Optimization Algorithm (SAR)" was hybridized with the prominent PSO. In addition, the scheduling procedure was carried out via empirical workflows with different tasks such as "Cybershake, Montage, and Epigenomics". The cloud scheduling workflow issue was simulated using the CloudSim tool. By contrasting the proposed methodology with several cutting-edge algorithms, the effectiveness of the developed model was confirmed.

In 2020, Sharma and Garg [7] have offered a "Harmony-Inspired Genetic Algorithm (HIGA)" to tackle the issue of energy-efficient task scheduling in CDC architecture. In order to efficiently detect both local and global optimal sectors without utilizing resources, the HIGA incorporated the exploration and exploitation characteristics of genetic algorithms. This led to rapid convergence. The suggested model was mainly designed to lower the workload and the energy consumption during the task scheduling process. The HIGA improved energy efficiency while using fewer resources. The rack components were turned off to lower the cooling energy. The stimulation outcome was evident that the proposed HIGA offered high energy savings and an increase in makespan with minimal computational overhead.

In 2021, Sohaib *et al.* [8] have recommended a hybrid-ant genetic algorithm for scheduling tasks. The suggested algorithm differentiated tasks and computer programs into smaller units and integrated the elements of the "genetic algorithm" and the "ant colony algorithm". Following task distribution, pheromones were integrated into virtual machines. The suggested technique effectively decreased the size of the solution space by partitioning the tasks into various groups and by determining the active virtual nodes. The faster convergence and response times were offered by the minimal solution space of the proposed algorithm. The developed model was used to lower the duration of workflows and tasks. The suggested technique reduced execution time and overall data center expenses.

B. Problem statement

The major problem in cloud data centers is considered energy-efficient task scheduling, where there is a need to minimize energy utilization and makespan for maximizing the performance of the cloud. This issue must be addressed, and thus, recent researchers are focused on designing new energy-efficient task scheduling approaches with the adoption of intelligent algorithms like meta-heuristic and deep learning approaches. However, these techniques also suffer from higher execution time or overhead due to the redundant solutions. The recent task allocating approaches in the cloud are reviewed in Table I. The genetic algorithm [1] performance of the designed model is enhanced by achieving lower execution overhead energy consumption, enhancing the makespan and reaching higher training accuracy by maintaining a lesser number of active racks. It is not suitable for allocating workflow applications with a group of individual tasks. Dynamic scheduling scheme [2] minimizes energy consumption by efficient dynamic task scheduling and also reduces the mean response time, improves the task guarantee ratio, and improves the overall scheduling efficiency. Although it achieves superior performance in task scheduling, it does not perform task failure predictions. Adaptive simulated-annealing-based bi-objective differential evolution [3] achieves lower energy cost and speed of convergence, enhances the diversity of Pareto-optimal individuals and reduces dynamic energy consumption. It

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suffers from processing complicated scenarios with more number of cloud data centers. The CSRSA [4] minimizes maintenance and operation costs, minimizes heat generation, and also reduces energy consumption, and, efficiently performs load balancing and saves energy. It is not applicable for large scale data centers. Hybrid optimization [5] has achieved superior efficiency regarding utilization, efficiency, waiting time, execution time and overall production time and the overall performance of the task scheduling approach is enhanced. It suffers from convergence issues. MOHPSO [6] achieves higher performance improvement regarding metrics like cost, makespan, and load balancing. It faces complications regarding a lower convergence rate. HIGA [7] reduces the execution overhead, improves the application performance regarding makespan, and reduces the execution time complexity. It does not solve the temperature effects. Hybrid and genetic algorithm [8] reduces the running time of the tasks and workflows and also minimizes the response time and convergence time. The dependencies among tasks are not addressed. This review helps us to suggest a new task scheduling approach in a cloud with the aim of suggesting novel techniques.

III. THE PRINCIPLE BEHIND THE TASK SCHEDULING PROCESS WITH OPTIMAL LOAD BALANCING IN CLOUD COMPUTING

A. Task Scheduling in Cloud Computing: Problem Formulation

The cloud system consists of several nodes, and they are associated with high heterogeneity and complexities. The total amount of tasks is raised with an increase in the count of users in the cloud platform. In the cloud era, efficient task allocation is a complex issue. The safety administration, resource organization, user administration and task supervision is the important consideration of the cloud platform layer. The cloud software application and communal interfaces are integrated into the cloud application layer. The task allocation process splits the task if the volume of the task is too high. Initially, the sub-tasks are generated by splitting the task given by the user. Further, the task and the virtual machine are mapped together by considering the difference of sub-tasks. Some specific techniques is considered to arrange the task o to the heterogeneous virtual nodes represented as n . The sub-task derived from the main tasks given by the user is indicated as $U = \{U_1, U_2, .. U_o\}$. These sub-tasks are assigned to the virtual machines of the cloud that is represented as $W = \{W_1, W_2, \dots W_n\}$. The virtual machine and the task are mapped for restricting the execution of sub-tasks in various virtual machines, and it is indicated in Eq. (1).

$$UW_{mapping} = \begin{Bmatrix} U_1W_1 & U_2W_1 & \cdots & U_oW_1 \\ U_1W_2 & U_2W_2 & \cdots & U_oW_2 \\ \vdots & \vdots & \vdots & \vdots \\ U_1W_n & U_2W_n & \cdots & U_oW_n \end{Bmatrix} \quad (1)$$

Here, the mapping in the middle of the virtual nodes and the task is represented as U_oW_n . The QoS, proper resource consumption and tiny implementation time are achieved by this task allocation process.

The fundamental structure of task allocation in a cloud platform is depicted in Fig. 1.

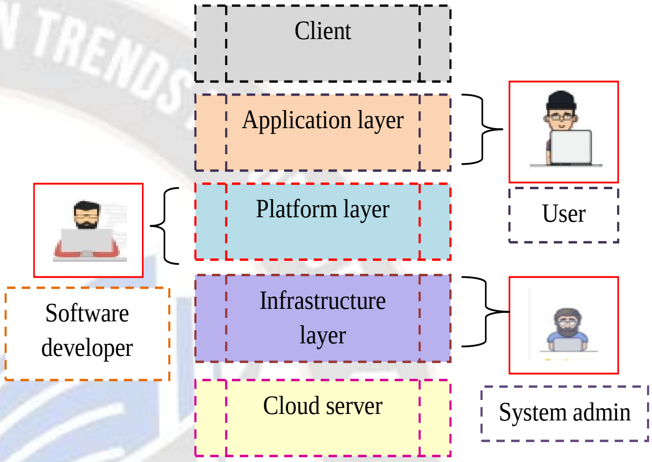

Figure 1. Basic structure of resource allocation in cloud platform

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TABLE I. USES AND LIMITATIONS OF TRADITIONAL TASK SCHEDULING APPROACHES IN THE CLOUD

Author [citation]	**Methodology**	**Features**	**Challenges**
Sharma and Garg [1]	Genetic algorithm	• The performance of the designed model is enhanced by achieving lower execution overhead energy consumption and enhancing the makespan. • It reaches higher training accuracy by maintaining a lesser number of active racks.	• It is not suitable for allocating workflow applications with a group of individual tasks.
Marahatta *et al.* [2]	Dynamic scheduling scheme	• This model minimizes energy consumption by efficient dynamic task scheduling and also reduces the mean reaction instance, improves the task assurance ratio, and improves the overall scheduling efficiency.	• Although it achieves superior performance in task scheduling, it does not perform task failure predictions.
Yuan *et al.* [3]	Adaptive simulated-annealing-based bi-objective differential evolution	• It achieves lower energy cost speed of convergence and enhances the diversity of Pareto-optimal individuals. • It reduces the dynamic energy consumption.	• It suffers from processing complicated scenarios with more number of cloud data centers.
Lu and Sun [4]	Clonal Selection Resource Scheduling Algorithm (CSRSA)	• It minimizes the maintenance and operation costs, minimizes the heat generation, and also reduces energy consumption. • It efficiently performs the load balancing and saves energy.	• It is not applicable for large scale data centers.
Sha and Santhosh [5]	Hybrid optimization	• It has achieved superior efficiency regarding utilization, efficiency, waiting time, execution time and overall production time. • The overall performance of the task scheduling approach is enhanced.	• It suffers from convergence issues.
Kakkottakathet *al.* [6]	MOHPSO	• It achieves higher performance improvement regarding metrics like cost, makespan, and load balancing.	• It faces complications regarding a lower convergence rate.
Sharma and Garg [7]	HIGA	• It reduces the execution overhead and improves the application performance regarding makespan. • It reduces the execution time complexity.	• It does not solve the temperature effects.
Sohaibet *al.* [8]	Hybrid ant genetic algorithm	• It reduces the management time of the tasks and workflows. • It also minimizes the response time and convergence time.	• The dependencies among tasks are not addressed.

B. Proposed Task Scheduling Model in Cloud Computing

The efficiency of the cloud structure is enhanced by the task allocation process. In the cloud environment, profit can be gained by dispersing the tasks to the virtual resources. The conventional techniques utilize a huge quantity of resources for the task allocation process. Furthermore, the conventional technique takes more cost and time for the task allocation process, so it isn't easy to fulfill the requirements of the clients. Besides, the handling time of the conventional task scheduling model is too high. In addition, the previous technique does not consider important attributes like reliability and availability in the task arrangement process. Thus, it affects the effectiveness of the cloud-based services. Existing techniques overutilize the resources, which leads to the degradation of cloud service performance. The conventional task scheduling models take more time to distribute the complex tasks to the virtual resource of the cloud. Moreover, existing techniques do not have the capacity to identify the sequence of tasks, so it does not satisfy the requirements of the customer in the stipulations of QoS. Thus, the intelligent heuristic-based task scheduling model in the cloud era is designed to fix the difficulties. The structural outline of the heuristic-assisted task scheduling framework is characterized in Fig. 2.

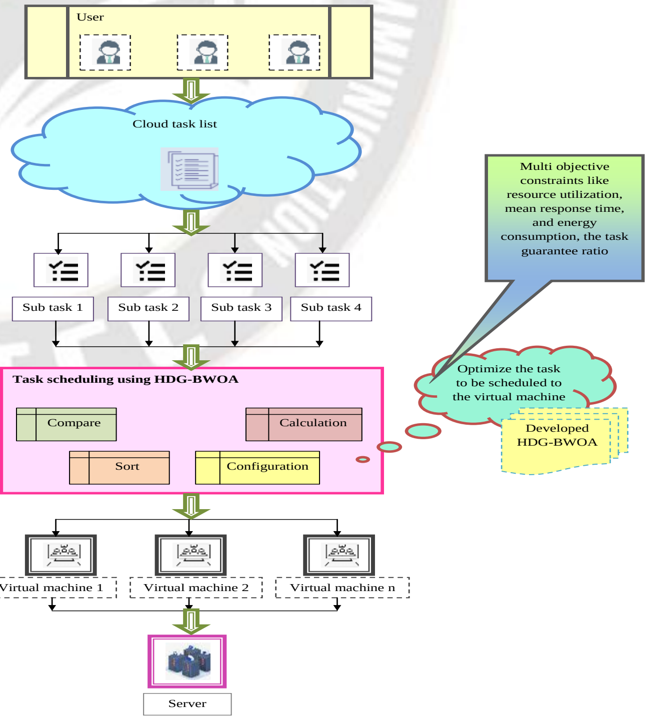

Figure 2. Structural outline of the heuristic-assisted task scheduling framework

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The hybrid heuristic-assisted task scheduling model is offered to assign the tasks to the appropriate virtual nodes of the cloud so that the task can be completed within a particular time without affecting the efficacy of the system. The developed task allocation approach assigns the top-priority task to the cloud for rapid execution. The suggested task scheduling model also appraises the load of the virtual nodes in the cloud for scheduling the tasks based on the capacity of the virtual machine. The user can give an assortment of tasks to the cloud structure. The received tasks are available in various sizes and types. After that, the collected task from the user is divided into sub-tasks based on the importance and execution time. After dividing the collected task into subtasks, the offered HDG-BWOA is grasped to allocate the task to the virtual resource of the cloud. In this process, the recommended HDG-BWOA optimizes the task to be allocated for the virtual machine; hence, the "mean response time, resource utilization, and energy consumption" is lowered. Additionally, the "task guarantee ratio" is highly maximized by the optimization process. The developed task scheduling algorithm considers the adequacy of the virtual resource, so the overloading action of the virtual resource is greatly neglected. Moreover, the task can be finished within a specified period because of the suggested task scheduling model. At last, the results of the p[resented model are correlated with the existing approaches to find the usefulness of the explored task scheduling with the load balancing model.

IV. Development of Hybridized Darts Game-based Beluga Whale Optimization as Efficient Task Scheduling Algorithm

A. DGO

The DGO [26] is the game-based optimization algorithm that mainly mimics the rules of the darts game.

The darts game is a simple game, and it is played by all genders and all age people. The dashboard and darts are the most important tools for the darts game.

Arithmetic design: The matrix is employed to design the population of players. In this matrix, the traits of the player is indicated in the column of the matrix, and the players are indicated in the row of the matrix. Here, the count of the problem variable and the count of columns in the matrix is considered as same.

The useful information is obtained by placing the term Y_j in the fitness function, and it is specified in the below expression.

$$G_{BEST} = mimum(FIT)_{O\times 1} \tag{2}$$

$$W_{BEST} = W(place\ of\ mimum(FIT), 1:n) \tag{3}$$

$$G_{WORST} = mximum(FIT)_{O\times 1} \tag{4}$$

$$W_{WORST} = W(place\ of\ mimum(FIT), 1:n) \tag{5}$$

$$G^o = \frac{FIT - G_{WORST}}{\sum_{k=1}^{O}(FIT_k - G_{WORST})} \tag{6}$$

$$Q_j = \frac{G_j^o}{mxi(G^o)} \tag{7}$$

Thus, the excellent variable is pinpointed as W_{BEST}, the best fitness function is elucidated as G_{BEST}, for the player j, the probability function is termed as Q_j, the normalized fitness function is signified as G^o, the worst fitness function is pinpointed as G_{WORST}, and the worst variable is represented as W_{WORST}.

The dartboard consists of diverse scores with a total of 82 areas. At each iteration process, the player can throw the darts in three times. The player's skill and the chance are used to analyze the location of the darts in the dartboard.

For each player, the throwing score is identified by Eq. (8) to Eq. (9).

$$D_j = circle(82\times(1 - Q_j)) \tag{8}$$

$$TD_j = \begin{cases} T(1:D), rdnu < Q_j \\ T(D+1:82), else \end{cases} \tag{9}$$

$$t_j = TD_j(l)\ and\ 1 \le l \le 82 \tag{10}$$

$$t_j^o = \frac{\sum_{flip}^{3} t_j^{flip}}{180} \tag{11}$$

Here, for the player j, the score for each hurl is represented as t_j, score candidates are indicated as TD_j, the normalized score of the player is delineated as t_j^o, the score matrix T is arranged into lower order.

The values of the issue variable and the innovated status of the player are indicated in Eq. (12).

$$W_j = W_j + rdnu(1,n)\times(W_{BEST} - 3t_j^o W_j) \tag{12}$$

Here, the innovated status of the player is represented as W_j.

The pseudocode of the DGO is elucidated in Algorithm 1.

Algorithm 1: DGO
Begin
Develop the primary population of the player
Find the fitness value
Upgrade the W_{BEST}, W_{WORST}, G_{WORST}, G_{WORST} by Eq. (2) to Eq. (5).
Upgrade the Q_j, and G^o using Eq. (6) and Eq. (7).
Find the t_j^o using Eq. (8) to Eq. (11).
Upgrade the W_j using Eq. (12).
Get best solution
End

B. BWO

The BWO [27] is the swarm-based Meta optimization algorithm. It is modeled on the basis of the behavior of the beluga whales. The optimization problem is easily solved by the BWO. The BWO is implemented in three phases, namely investigation, exploitation and whale fall.

Motivation: The beluga whale mostly lives in the sea, and it produces diverse sounds, so it is referred to as the canary of the sea. The adult whales are available in white color. The weight of the beluga is about 1500kg, and the length of the beluga whale is around 3.5 to 5.5m. The hearing and vision capabilities of the beluga are too sharp. The beluga whales produce diverse sounds for the hunting process. The beluga whales are mostly distributed in the Arctic and subarctic regions of the ocean. In some places, the beluga whales are sheltered in aquariums.

Arithmetical design of the BWO: The swimming, hunting and the whale fall activities of the beluga whale is employed for modeling the BWO. The investigation and the exploitation phases are also available in the BWO. The global searching capability of the beluga whale is modeled in the investigation of the BWO. Consequently, the local searching capability of the beluga whale is elaborated in the exploitation phase of the BWO. In this BWO, the beluga are examined as the search agents, and they adopt their corresponding position vector for causing displacement in the search area. The spot of the beluga whales is altered by the prospect of the whale falling in the BWO. In the BWO, the search agents are represented in the matrix W and the fitness value is indicated in the matrix E_Y.

The balance factor A_g is used by the BWO for converting the investigation to the exploitation stage, and it is illustrated in Eq. (13).

$$A_g = A_0\left(1 - \frac{S}{2S_{\max}}\right) \tag{13}$$

Thus, the value of the balance element A_g is greater than 0.5, it loads to the development of the exploration stage in BWO. The excellent iteration is constituted as $S_{\max}$, the present iteration is signified as S, at every iteration process, the value of A_0 is altered in the middle of $[0,1]$. If the value of $A_g \le 0.5$, then the exploitation stage is implemented. The value of A_g decreases from $[0,1]$ to $[0,0.5]$, because of an increase in iteration S. When the value of iteration S is augmented, it loads to an increase in the probability of the exploitation phase.

Investigation phase: The swimming traits of the beluga are used to examine the exploration phase of the BWO. Under the diverse position, the beluga whale performs the social sexual behavior. The mirrored manner of the two beluga is employed to determine the location of the search negotiator. The location of the beluga is upgraded based on the above consequences, and it is signified in Eq. (14).

$$\begin{cases} W_{j,k}^{s+1} = W_{j,O_k}^{s} + \left(W_{q,O_1}^{s} - W_{j,O_k}^{s}\right)(1+q_1)\sin(2\pi q_2), \ k = even \\ W_{j,k}^{s+1} = W_{j,O_k}^{s} + \left(W_{q,O_1}^{s} - W_{j,O_k}^{s}\right)(1+q_1)\cos(2\pi q_2), \ k = odd \end{cases} \tag{14}$$

Thus, for the beluga whale j and at the dimension k, the fresh spot of the beluga whale is represented as $W_{j,k}^{s+1}$, at the dimension c, the selected arbitrary number is represented as O_k, and $k = 1,2..c$. At the dimension O_k, the location of the beluga j is expressed as W_{j,O_k}^{s}. The existing position of j^{th} and q^{th} beluga whale is represented as W_{j,O_k}^{s}, and W_{q,O_1}^{s} correspondingly. The random number in the middle $[0,1]$ is represented as q_1, and q_2 respectively. The average fins of the reflected beluga in the direction of the facade is illustrated as $\sin(2\pi q_2)$, and $\cos(2\pi q_2)$ respectively. The mirroring trait of the beluga whales while in the swimming position is reflected by the position value updated by the odd and even numbers. The erratic operator in the exploitation phase is enriched by the two random numbers q_1 and q_2, respectively.

Exploitation phase: The poaching characteristics of the beluga whale are designed in the exploitation stage of the BWO. The poaching action of the beluga whales is done in a cooperative manner, which means the information is passed to the adjacent best whale for executing the poaching process. The convergence rate in the exploitation stage of the BWO is enhanced by introducing the levy flight operator. This operator is used by the beluga whales for catching the target prey, and it is elucidated in Eq. (15).

$$W_j^{S+1} = q_3 W_{BEST}^{S} - q_4 W_j^{S} + B_1 \cdot K_G\left(W_q^{S} - W_j^{S}\right) \tag{15}$$

Here, the new spot of the beluga j is represented as W_j^{S+1}, the present iteration is represented as S, and the existing location of the arbitrary beluga is characterized as W_q^{S}. The existing spot of the beluga j is indicated as W_j^{S}, the arbitrary number is depicted as q_3, and q_4 respectively, and it is lies in the middle of $[0,1]$, the best position of the beluga whale is indicated as W_{BEST}^{S}, and the intensity of the levy flight is identified by the arbitrary leap durability and it is indicated in Eq. (16).

$$B_1 = 2q_4\left(1 - \frac{S}{S_{\max}}\right) \tag{16}$$

Eq. (17) gives the expression for the levy flight operator K_G.

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$$K_G = 0.05 \times \frac{t \times \varpi}{|u|^{\frac{1}{\rho}}} \quad (17)$$

$$\varpi = \left(\frac{\Im(1+\rho) \times \sin\left(\frac{\pi\rho}{2}\right)}{\Im\left(\frac{(1+\rho)}{2}\right) \times \rho \times 2^{\left(\frac{\rho-1}{2}\right)}} \right)^{\frac{1}{\rho}} \quad (18)$$

Here, the absent factor is represented as ρ, and it is taken as 1.5; the usually dispersed arbitrary numbers are indicated as t, and u correspondingly.

Whale fall: The beluga whale is attacked by the polar bear, humans and other killer whales during the poaching and migration process. The beluga whale passes the information to other whales and intelligently escapes from the threats. Sometimes, the beluga whales fall on the sea bed because of the threats caused by the killer whales. The falling of whales under the sea bed is known as whale fall. The fallen body of the whale is consumed by the sharks and other animals in the sea. The remaining bones of the beluga whale are consumed by the bacteria and coral reefs of the ocean. The location of the beluga whales is updated by considering the dimension of the step in the whale fall action, the dimension of the population constant, location of the beluga are represented in Eq. (19).

$$W_j^{S+1} = q_5 W_j^S - q_6 W_j^S + q_7 W_{step} \quad (19)$$

Here, the dimension of the step in the whale fall process is represented as W_{step} and the random number is represented as q_5, q_6 and q_7 in $[0,1]$. The value of W_{step} is determined by Eq. (20).

$$W_{step} = (t_c - k_c)\exp\left(-B_2 \frac{S}{S_{\max}}\right) \quad (20)$$

Here, the upper and the lower boundary of the variable are represented as t_c *and* k_c, respectively, the chance of whale fall and the size of the population is mainly rely on the step factor B_2, and it is identified by Eq. (21).

$$B_2 = 2V_g * m \quad (21)$$

Here, the chance of whale fall is represented as V_g, and it is identified by Eq. (22).

$$V_g = 0.1 - 0.05 \frac{S}{S_{\max}} \quad (22)$$

Here, the chance of whale fall is calculated in linear form, and its values is taken as 0.1 at the primary iteration. Further, the chance of whale fall is turned down to 0.05 at the final iteration. The pseudocode of the conventional BWO is given in Algorithm 2.

Algorithm 2: BWO
Initialize the population and maximum iteration size
While $S \le S_{\max}$ do
Find the balance factor A_g using Eq. (13).
Get the chances of whale fall using Eq. (22).
For entity beluga W_j do
If $A_g(j) > 0.5$
Execute the investigation phase and update the position of the beluga whale using Eq. (14).
Else if $A_g(j) > 0.5$
Execute the development phase and upgrade the location of the beluga whale using Eq. (15).
End if
Verify the boundary condition of the new position and find the fitness values
End for
For individual beluga
Execute the whale fall action
If $A_g(j) \le W_g$
Find the step factor B_2 using Eq. (21).
Evaluate the step size W_{step} using Eq. (20).
Verify the boundary condition of the new spot and find the fitness values
End if
End for
Calculate the present best solution.
$S = S + 1$
End while
Get best solution

C. Developed HDG-BWO

The developed HDG-BWO is formed by incorporating the conventional DG and BWO. The total amount of task that are allocated to the virtual resource is optimized by the HDG-BWO. So it loads to the minimization of "resource utilization", "mean response time", and "energy consumption" in the task-scheduling process. In addition to that, the task guarantee ratio is maximized as a consequence of the optimization process. The overall processing time for the virtual machine is greatly turned down by the task allocation process. The existing BWO is the swarm-aided algorithm that effectively conquers the optimization problem, and the convergence rate and robustness of the BOW are very high. Yet, the discrete issues are not solved by the BWO, and it does not give effective optimization solutions for the big data application field. The DGO is a game-based optimization, and it is simple to understand. In addition, the exploration and exploitation capabilities are really well. Yet, the global optimal solutions are not solved by the DGO. So, the new HDG-BWO is developed to crack the aforementioned difficulties. The new HDG-BWO is executed by updating the location using the upcoming conditions. The maximum iteration and the current iteration are indicated as

$S_{\max}$, and S respectively. If the present iteration S is divisible by 7 and 9, then the position W_j is upgraded by the DGO. Otherwise, the position W_j^{S+1} is updated by the BWO. The developed HDG-BWO can easily provide a globally optimal solution due to the position updating process. In addition, the discrete issues are efficiently handled by the developed HDG-BWO.

The pseudocode of the developed HDG-BWO is given in Algorithm 3, and the flow indication is shown in Fig. 3.

Algorithm 3: HDG-BWO
Initialize the quantity of population $popu$ and greatest number of iteration $S_{\max}$
For $u = t \ to \ S_{\max}$
For $j = 1 \ to \ popu$
Upgrade the W_{BEST}, W_{WORST}, G_{WORST} and G_{WORST} by Eq. (2) to Eq. (5).
Find the balance factor A_g using Eq. (13).
Get the chances of whale fall using Eq. (22).
If S is divisible by 7 and 9
Modernize the position using W_j Eq. (12) of DGO.
Else
Upgrade the potion using W_j^{S+1} using Eq. (15) of BWO.
End if
End for
End for
Get best solution
End

V. OBJECTIVE FUNCTION FOR TASK SCHEDULING USING HYBRIDIZED DARTS GAME-BASED BELUGA WHALE OPTIMIZATION ALGORITHM

A. *Objective Function of Task Scheduling*

The objective function of task allocation is to lower the resource consumption, mean response time, and energy consumption in the task scheduling process and it is offered in Eq. (23).

$$obf = \arg\min_{\{T_n^{VM}\}} \left(RU + RT + EC + \frac{1}{TGR} \right) \tag{23}$$

Here, the task that has to be arranged to the virtual resource of the cloud is represented as T_n^{VM}. The resource utilization is elucidated as RU, the mean reaction time is pinpointed as RT, energy consumption is represented as EC and the task guarantee ratio is indicated as TGR.

The execution time must be minimal to execute the load balancing process, and the formula for the degree of imbalance is given in Eq. (24).

$$EJ = \frac{U(\max) - U(\min)}{U(avg)} \tag{24}$$

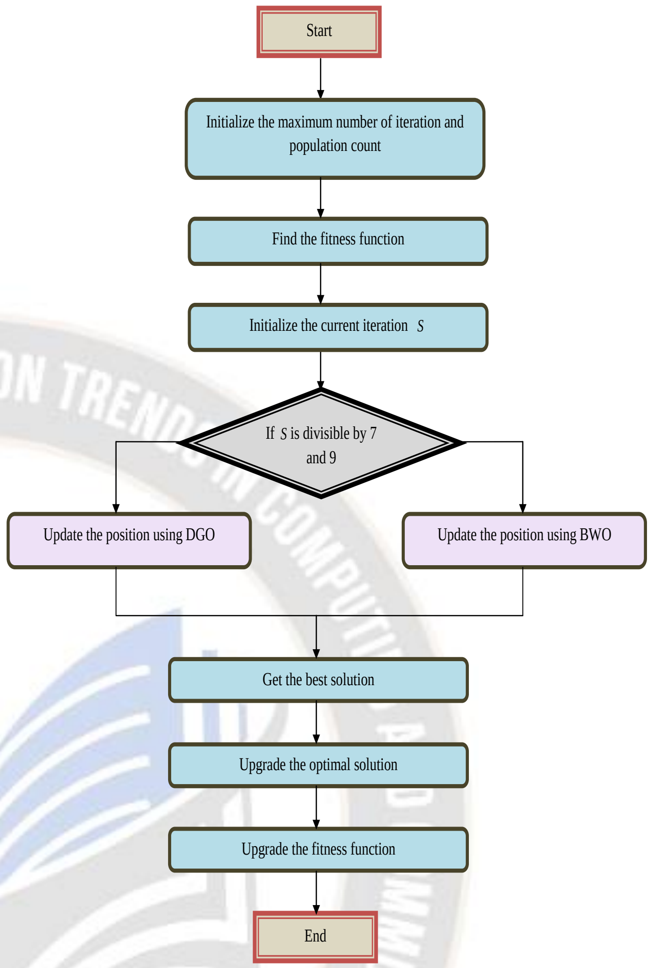

Figure 3. Flowchart of developed HDG-BWO

Here, the maximum, average and minimum execution times are represented as $U(\max)$, $U(avg)$, and $U(\min)$.

The solution illustration for the task scheduling process is denoted in Fig. 4.

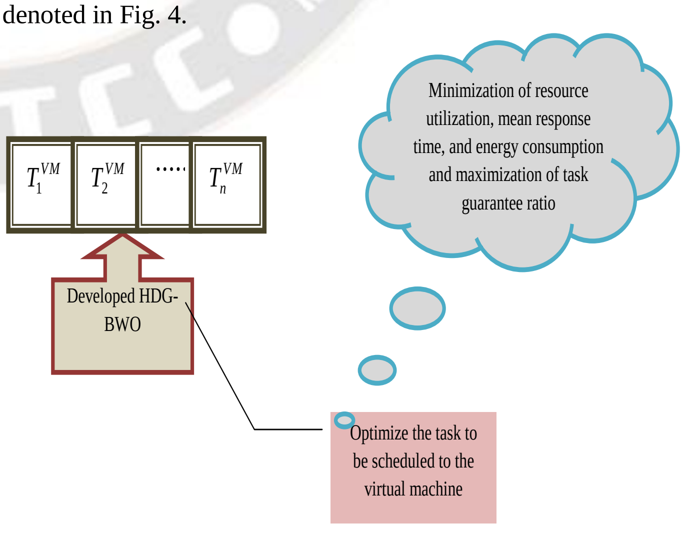

Figure 4. Solution diagram of the task scheduling process

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B. *Description of Task Scheduling Objective Constraints*

The objective constraints in the task allocation process are elaborated as follows.

Resource Utilization: It states the total amount of resources utilized in the task allocation process, and it is offered in Eq. (25).

$$RU = \frac{\sum_{j=1}^{n} DU_j}{Makespan * n} \tag{25}$$

Here, the task completion time is represented as DU and the total count of virtual machines is specified as n.

Mean response time RT: The time consumed by the load balancing model in the cloud architecture is elucidated as mean response time, and it is given in Eq. (26).

$$RT = \sum_{j=1}^{o} DU + TC \tag{26}$$

Here, the term TC denotes the capitulation time of the task and task completion time is represented as DU.

Energy consumption: It is defined as the summation of energy used in the task allocation process (active energy) and the energy utilized by the virtual machine when it is in an inactive state (inactive energy). This is expressed in Eq. (27).

$$EC = EC(act) + EC(inact) \tag{27}$$

Here, the active energy is represented as $EC(act)$ and the inactive energy is represented as $EC(inact)$.

Task guarantee ratio: It is the ratio of the throughput to the total number of completed tasks, and it is signified in Eq. (28).

$$TGR = \frac{throughput}{TNCT} \tag{28}$$

Here, the term $TNCT$ represents the total number of completed tasks.

VI. RESULTS AND DISCUSSION

A. *Simulation setup*

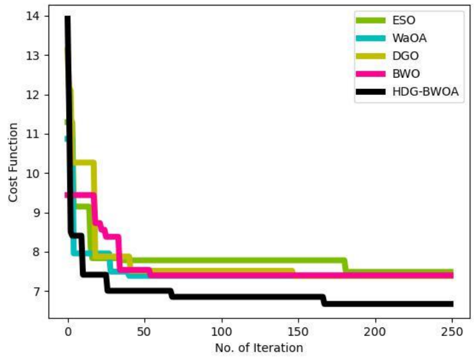
The HDG-BWO-based task allocation model with optimal load balancing was tested in the Python platform. In this analysis process, the maximum iteration and number of population were taken as 250 and 10, correspondingly. Here, the chromosome length was taken the same as a number of tasks. Conventional algorithms like Egret Swarm Optimization (ESO) [28], Walrus Optimization Algorithm (WaOA) [29], Darts Game Optimizer (DGO) [26] and Beluga Whale Optimization (BWO) [27] were employed in the analysis process to identify the efficacy of the developed model. The analysis process was effectively accomplished by the five configurations. The configuration details adopted in the HDG-BWO-based task scheduling model with optimal load balancing are elucidated in Table II.

B. *Cost function analysis*

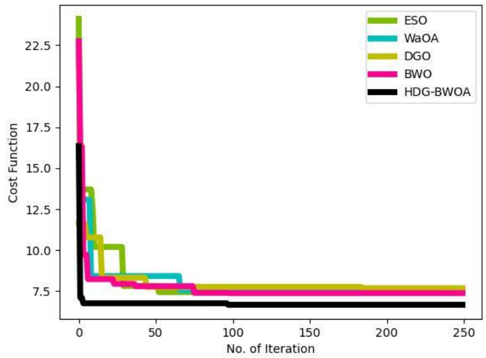
The convergence examination of the explored HDG-BWO-based task scheduling process is specified in Fig. 5. When the number of iterations is raised, the convergence rate of the HDG-BWO-based task scheduling process decreases. When the iteration value is considered as 100, the convergence rate of the HDG-BWO-based task scheduling framework is better than ESO, WaOA, DGO and BWO with 31.66%, 25%, 30% and 26.66%. Thus, the developed HDG-BWO-based task scheduling structure shows better convergence in the task scheduling process.

TABLE II. CONFIGURATION DETAILS OF THE RECOMMENDED HEURISTIC-BASED OPTIMAL TASK SCHEDULING IN A CLOUD ENVIRONMENT

“Configuration”	Number of servers	Memory size	CPU	Number of tasks	Memory size	CPU
1	10	5GB to 7 GB	150 GB to 180 GB	90	950GB to 1.9 GB	25GB to 35GB
2	25	13GB to 18GB	310GB to 340 GB	180	4GB to 8 GB	78GB to 98 GB
3	45	30GB to 34 GB	645GB to 685 GB	285	11GB to 14 GB	118GB to 138GB
4	73	60GB to 65 GB	800GB to 825 GB	385	18 GB to 23GB	148 GB to 150 GB
5	95	78GB to 83 GB	5GB to 7 GB	490	28GB to 32GB	173GB to 178 GB



(a)



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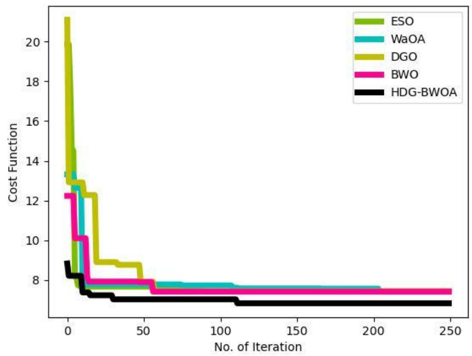

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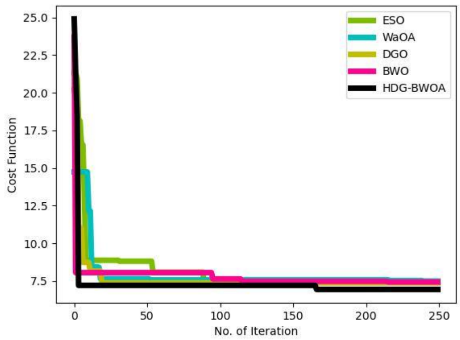

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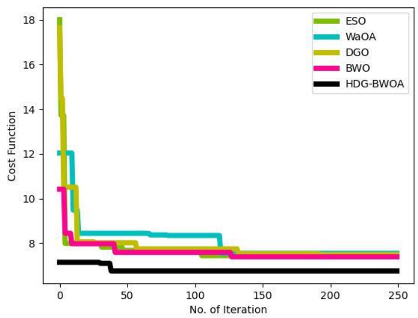

(e)

Figure 5. Convergence assessment of the heuristic-based task scheduling process for (a) Configuration 1, (b) Configuration 2, (c) Configuration 3, (d) Configuration 4, (e) Configuration 5

C. Performance evaluation of the suggested model using positive indices among conventional algorithms

The performance assessment of the explored HDG-BWO-based task scheduling process based on the positive indices is provided in Fig. 6. As mentioned in Fig. 6 (g), the HDG-BWO-based task scheduling process achieves higher throughput than the ESO, DGO, WaOA and BWO with 20%, 18.18%, 9.85% and 23.80% at the configuration 3. Therefore, the throughput rate of the developed HDG-BWO-based task scheduling model is raised than the conventional algorithms.

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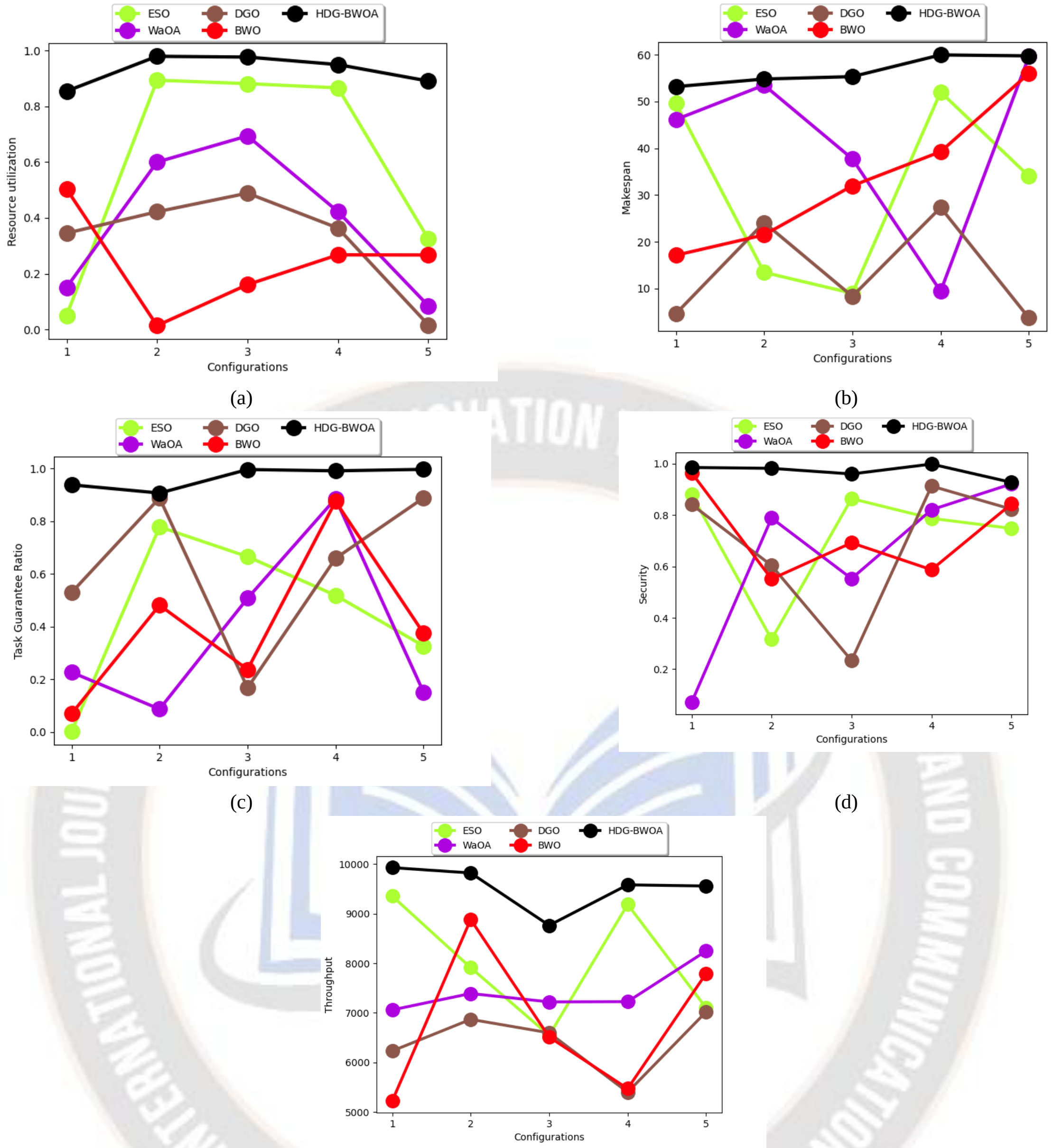
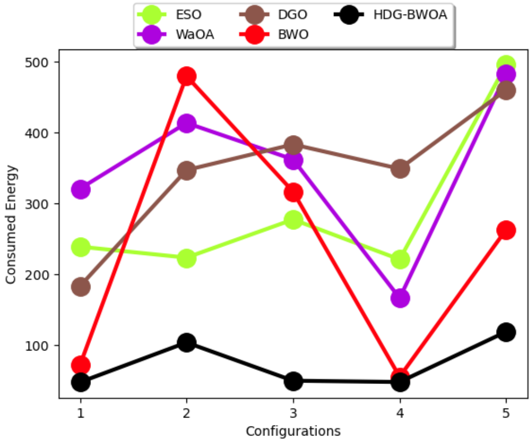


(g)

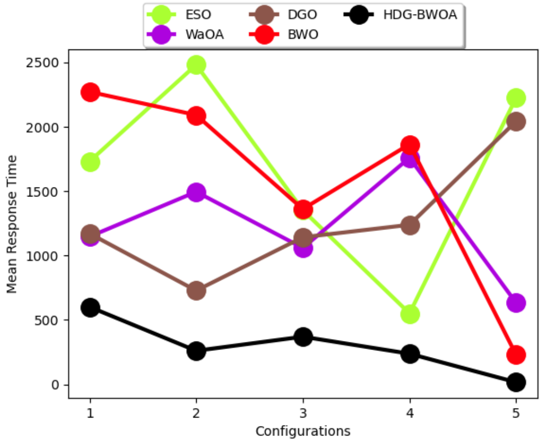
Figure 6. Performance determination of the heuristic-based task scheduling process for (a) Resource utilization, (b) Makespan, (c) Task guarantee ratio, (d) Security, (e) Throughput

D. Performance assessment of the developed model using consumed energy and mean response time

The performance assessment of the developed model on consumed energy and mean response time is designated in Fig. 7. At configuration 2, the mean response time of the developed HDG-BWO-based task scheduling process is shortened than the ESO, DGO, WaOA and BWO with 90%, 68.75%, 83.33% and 88.09%. Similarly, the energy consumption of the developed HDG-BWO-based task scheduling process is very low as compared to the usual algorithm. So, the developed HDG-BWO-based task scheduling process consumes a very low response time than the existing algorithms.



(a)



(b)

Figure 7. Performance evaluation of the heuristic-based task scheduling process for (a) Consumed energy, (b) Mean response time

E. Statistical examination of several algorithms

The statistical examination of the HDG-BWO-based task scheduling model is arranged in Table III. For configuration 1, the best measure of the HDG-BWO-based task scheduling model is upraised with 12.14%, 10.64%, 10.68% and 10.91%. So, the performance of the suggested HDG-BWO-based task allocation model is superior to the existing algorithms.

TABLE III. STATISTICAL EVALUATION OF THE SUGGESTED HEURISTIC-AIDED TASK SCHEDULING MODEL THROUGH SEVERAL ALGORITHMS

ALGORITHMS	ESO [28]	WaOA [29]	DGO [26]	BWO [27]	HDG-BWO
Configuration 1					
BEST	7.485243	7.386536	7.383864	7.398601	6.67225
WORST	11.29473	10.86898	13.11406	9.438971	13.9244
MEAN	7.821605	7.502046	7.717367	7.626955	6.951844
MEDIAN	7.781209	7.386536	7.512571	7.398601	6.851971
STANDARD DEVIATION	0.550523	0.460835	0.852244	0.572806	0.629812
Configuration 2					
BEST	7.441174	7.40804	7.678964	7.376632	6.667063
WORST	24.10892	15.76553	11.65105	22.75028	16.34928
MEAN	7.972295	7.931065	8.0022	7.693664	6.743656
MEDIAN	7.441174	7.55756	7.759791	7.376632	6.667063
STANDARD DEVIATION	1.66709	1.142747	0.804425	1.282697	0.61137
Configuration 3					
BEST	7.422877	7.404899	7.431248	7.406803	6.821539
WORST	19.87506	13.31543	21.10574	12.23289	8.826721
MEAN	7.698397	7.827388	8.038958	7.677048	6.979189
MEDIAN	7.422877	7.570919	7.431248	7.406803	6.821539
STANDARD DEVIATION	1.415384	1.061197	1.601816	0.818233	0.298116
Configuration 4					
BEST	7.413741	7.496861	7.376933	7.436125	6.940097
WORST	21.32683	14.74146	20.20608	23.67385	24.90353
MEAN	8.141291	7.927857	7.623239	7.769633	7.292114
MEDIAN	7.46266	7.583361	7.376933	7.483629	7.210348
STANDARD DEVIATION	1.973923	1.454961	1.427965	1.045217	1.606721
Configuration 5					
BEST	7.422267	7.543718	7.489383	7.389534	6.755631
WORST	18.00856	12.03476	17.64631	10.41462	7.143281
MEAN	7.68976	8.112125	7.887447	7.601801	6.813076
MEDIAN	7.43896	7.543718	7.741969	7.586814	6.755631
STANDARD DEVIATION	0.955224	0.921595	1.039926	0.425251	0.135882

VII. RESULTS AND DISCUSSION

The offered heuristic-based task allocation with an optimal load balancing model was utilized to allocate the tasks to the appropriate virtual nodes for finishing the task within the limited time period. Here, the user can provide various tasks to the cloud platform. This task was divided into sub-tasks to effectively carry out the task allocation process. These sub-tasks were assigned to the virtual machine of the cloud using the HDG-BWO. This HDG-BWO optimizes the tasks that have to be allocated to the virtual resource for lowering the "mean response time, resource utilization and energy consumption" in the task scheduling process. At configuration 2, the mean response time of the developed HDG-BWO-based task scheduling process was less than the ESO, DGO, WaOA and BWO with 90%, 68.75%, 83.33% and 88.09%. So, the developed models effectively schedule the task to the virtual nodes by employing the loading capacity of the virtual machine.

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