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Original Article

Secure Resource Allocation in the Cloud for Seamless Transactions using Average Sample Learning Strategy-based Horse Herd Optimization

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Abstract - *Recently, optimization of the resource allocation in Cloud Computing (CC) has become more important because of an increase in users, who send or access data from the cloud. Resource allocation is performed based on Quality of Service (QoS) parameters of cloud services that optimize the solutions for allocating resources according to the scheduled tasks to reduce overall costs for end-users/services. However, the existing resource allocation failed to allocate the resource efficiently, making it difficult to ensure secure resource allocation during dynamic demand fluctuations. To overcome this limitation, an Adaptive Sample Learning strategy-based Horse Herd Optimization algorithm (ASL-HHO) model is employed for secure resource allocation within cloud environments. The proposed HHO algorithm allocates additional resources with security measures when a threat is detected and ensures secure transactions in small finance organizations. This defense structure for resource allocation ensures data integrity and privacy, which are crucial for financial transactions. To ensure secure and efficient resource allocation in a cloud environment, the ASL-HHO algorithm-based resource allocation model incorporates the QoS parameters, which include trust, resource utilization, energy consumption, and makespan. Experimental results of the ASL-HHO algorithm attained efficient resource utilization for tasks 100, 200, and 500 are 2896, 3589, and 42741, which is higher when compared to existing resource allocation models such as Adaptive Multi- Objective-Teaching Learning Optimization (AMO-TLO).*

Keywords - *Adaptive Sample Learning strategy, Cloud Computing, Horse Herd Optimization Algorithm, Quality of Service, Resource allocation.*

1. Introduction

Cloud Computing (CC) is an advancement in information technology that allows users to access resources for task execution and share data/resources collaboratively across multiple computers. These CC resources are organized based on workload to ensure ideal usage of resources and their services to external users [1]. Nowadays, various companies across the world are heavily dependent on cloud resources to enhance their competitiveness, making it a major trend [2]. By utilizing the CC, several individuals and distinct organizations can access scalable resources like servers, storage, etc., for various applications in a shared pool [3, 4]. This helps the users to access data through convenient and dynamic resources that correspond to the tasks and workloads efficiently. The cloud architecture involves several computer systems and millions of heterogeneous computing resource servers; thus, an efficient resource allocation is essential to reduce energy waste [5-7]. Based on the environment and tasks/workloads, the resource allocation in the cloud is categorized as static and dynamic types [8, 9]. In static allocation, the resources are allocated before the execution starts, whereas dynamic allocation is used to allocate resources during the task/job execution.

The resource allocation is referred to as enabling the user requests to execute automatically without any direct intervention, where CC services are generally provided on demand due to time constraints [10]. Hence, resource scheduling should be designed to obtain maximum efficiency through optimal resource utilization in CC [11]. However, an efficient and energy-saving CC data center with optimized resources remains a challenging thing that impacts performance. Thus, the existing research used an adaptive resource allocation model for allocating the cloud resources efficiently according to workload and based on resource capacity [12]. Since the resources in the cloud are directly influenced by valuable Quality of Service (QoS) parameters, which also adapt the resource allocation model. Various research focused only on energy-efficient resource allocation in CC and did not consider security issues [13, 14]. The

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transaction data of organizations and small finance institutions using cloud servers is sensitive. In small finance organizations, seamless transactions are crucial to maintain customer trust and also ensure business operations through efficient resource allocation. Most of the existing resource allocation methods focused on improving speed and efficiency, but failed to adopt the dynamic workload changes to handle security threats in real-time cloud computing efficiently.

1.1. Problem Statement and Objective

However, the cloud environments are dynamic with changing workloads and resource availability, adapting resource allocation to maintain seamless transactions while ensuring security is a challenging task [15]. To overcome this limitation, an Average Sample Learning strategy-based Horse Herd Optimization (ASL-HHO) is proposed for secure resource allocation in the cloud for seamless transactions in small finance.

1.2. Contributions

The main contributions of this research are:

- An ASL-HHO algorithm is proposed for secure resource allocation in a cloud environment for seamless transactions in small organizations. The averaging process enables the algorithm to adapt more smoothly to these changes.
- The utilization of a sample learning strategy makes the HHO algorithm more resilient to dynamic changes in the cloud environment, such as fluctuating workloads and varying security threats.
- The proposed HHO algorithm optimizes the utilization of cloud resources by reducing unnecessary allocation and preventing over-provisioning. This leads to increased efficiency of cloud infrastructure, thereby making it cost-effective and ensuring financial institutions maintain seamless transactions in small finance.

This manuscript is organized with literature reviews in Section 2, followed by Section 3 with the proposed methodology. Section 3 describes the proposed resource allocation algorithm. Section 4 demonstrates the results and research findings. Section 5 depicts the conclusion of this manuscript.

2. Literature Review

Ali Moazeni et al. [16] developed a resource allocation model in CC based on a multi-objective optimization algorithm. The developed teaching-learning-based optimization model was incorporated with an adaptive multi-objective technique to improve the searching ability of the model. An advantage of a developed teaching–learning optimization algorithm adapted to the changing nature of the cloud effectively, which enhanced the balance in resource allocation. However, the adaptive nature of the developed optimization model was not sufficient to respond quickly to rapid changes in QoS requirements and emerging security threats.

Mohit Kumar et al. [17] designed a Spider Monkey Optimization (SMO) algorithm for effective research allocation in CC. The designed SMO algorithm was utilized to develop a trust-aware cloud resource allocation framework to validate the authenticity of end-users to enhance security. The designed SMO had the foraging behavior of spider monkeys that led to optimizing the allocation of cloud resources like memory and storage, effectively also reducing wastage. However, the designed SMO algorithm had slow convergence, which led to delays in resource allocation decisions.

Majid Alotaibi [18] explored a hybrid metaheuristic optimization model to allocate the resources in the cloud efficiently. The explored hybrid model was an integration of the Combined Spider and Honey Bee Optimization (CS-HBO) algorithm according to certain constraints like system failure, threshold distance, and balanced cluster usage for optimal resource allocation. An advantage of the explored CS-HBO-based resource allocation model is that it handles dynamic changes in the cloud environment due to the adaptable nature of the HBO algorithm. However, the explored hybrid model based on the CS-HBO algorithm conflicted with each other under certain conditions that made the model difficult to allocate the resources efficiently.

R. Mangalagowri andRevathiVenkataraman [19] presented an effective resource allocation model based on the adaptive Firefly Optimization (FFO) algorithm. The explored hybrid model was an FFO algorithm based on certain constraints, such as system failure, balanced cluster usage, threshold distance, and so on, for optimal resource allocation. However, the integration of FFO strategies and algorithms conflicts with each other, which can lead to less efficient resource allocation or slower convergence in certain scenarios.

Arun Kumar Sangaiah [20] represented a fuzzy-based metaheuristic optimization model for resource allocation in the cloud. The represented fuzzy-based model was an integration of a neural Fuzzy system and an Ant Colony Optimization (FACO) algorithm, which was used for allocation of cloud resources based on certain constraints to achieve optimal resource allocation. An advantage of the represented FACO algorithm is that it adapts to workload demands efficiently in the cloud environment. However, the represented neuro-Fuzzy model, which was integrated with ACO, had drawbacks that directly impacted inappropriate resource allocation or slower convergence in certain scenarios.

Hang Zhang et al. [21] developed a secure resource allocation model based on Deep Reinforcement Learning (DRL) in multi-cloud edge computing. The developed DRL model provided an optimal resource allocation scheduling policy based on action constraints. Additionally, the DRL model optimally learns policies from real-time feedback, which enabled the system to efficiently adapt to workload changes, security threats, and environmental factors. Bo Qi et al. [22] explored an intelligent multi-objective model for efficient resource allocation. For an optimal resource allocation, a Modified Feeding Birds Algorithm (MFDA) was integrated with DRL to improve adaptive resource allocation. The main advantage of this explored model was leveraging the historical and real-time data, which helped make more informed decisions than static and rule-based schedulers. Miaolei Deng et al. [23] designed a nature-inspired algorithm for workload optimization in cloud computing. The main objective of this model was to increase the assignment of tasks in the workload optimization technique, which helped improve the job distribution strategically to the virtual machines. Additionally, the designed nature-inspired algorithms iteratively updated the solutions based on feedback, which efficiently adapted to changing workloads and resource conditions. From the above literature review, it is observed that the existing resource allocation models based on multi-objective optimization, trust-aware metaheuristics, and DRL-based approaches focus on performance efficiency, adaptability, and workload optimization. However, the conventional models face limitations such as slow convergence and struggle to adapt to the dynamic workload changes and rapid quality of service variations. Also, the security integration remains partial with insufficient consideration of dynamic threat intelligence and attack-aware allocation of resources in cloud computing. Therefore, a significant research gap leads to the development of a secure and adaptive intelligent resource allocation framework for security, scalable and fast convergence, robust performance in dynamic cloud environments.

3. Methodology

In the cloud, a secure resource allocation based on quality of service parameters involves resource distribution that not only satisfies security requirements but also ensures efficiency and reliability. The proposed framework for secure resource allocation in the cloud is illustrated in Figure 1.

This secure resource allocation is crucial for maintaining integrity, availability of applications and data, and confidentiality in a cloud environment. The advantages of secure resource allocation prevent service disruptions, data breaches, and most importantly, unauthorized access, which has severe consequences for businesses and firms, leading to financial loss.

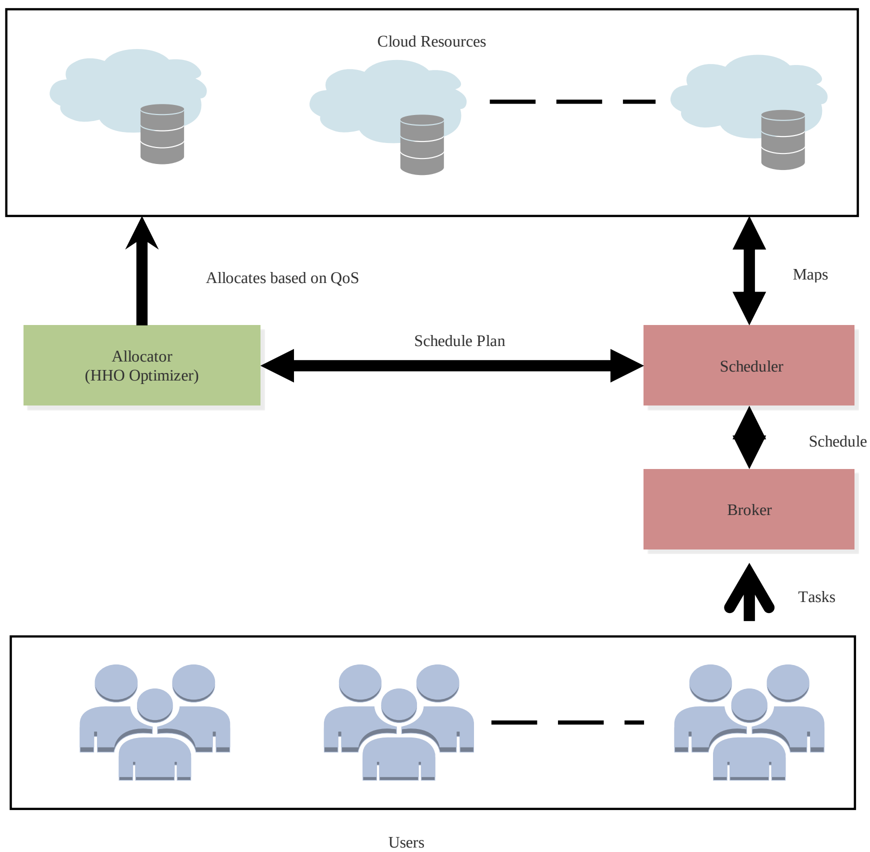

Fig. 1 Proposed resource allocation framework in the cloud

To perform secure resource allocation for small finance transactions in the cloud, initially, the data for resource allocation is acquired from some of the cooperative societies that are registered in India. The cooperative societies are registered under the 1904 Act initially for 5 to 6 years, which are utilized in this research and are depicted as follows: Agricultural Service Cooperative Society Ltd., Punjab (1905); Bilipada Service Cooperative Society Ltd., Orissa (1905); Government of India, Sectt. Cooperative Thrift & Credit Society (1905); Kanginhal Vyvasava Seva Sahakari Bank Ltd., Karnataka (1905); Kasabe Tadvale Cooperative Town Bank, Andhra Pradesh (1907); Rajahauli Village Bank, Jorhat, Assam (1904); Rohika Union of Cooperative Credit Societies Ltd., Bihar (1909); Triur Primary Agricultural Cooperative Bank Ltd., Tamil Nadu (1904). Additionally, some of the non-credit initiatives under this act are as follows: Triplicane Society in Madras that ran consumer stores; Weaver credit cooperatives in Dharwad and Hubli that provided credit in the form of yarn, and so on.

3.1. Authentication

An authentication process is performed to verify the authenticity of end-users by an improved multi-factor authentication mechanism in CC. Initially, users should submit their requests via the web or any other command-line interface. Then, the service provider verifies and allows only the legitimate users to access cloud resources. Also, this authentication process blocks unauthorized users and malicious requests, which means that the service providers deny access to illegal end-users, ensuring secure resource allocation in the cloud.

Rivest Shamir Adleman (RSA) and Advanced Encryption Standard (AES) are the encryption algorithms that are employed to encrypt the secret and public keys for the authentication process. Next, the user can send requests to the user services of the resource manager in a more secure way when compared with conventional security mechanisms. Finally, the HHO algorithm-based resource allocation model is employed in this research for secure resource allocation corresponding to the requested tasks and availability of Virtual Machines (VMs), which considers the quality of service parameters.

3.2. Proposed Resource Allocation Model

The role of a service provider in the cloud is to manage a large pool of VMs and allocate the user tasks to appropriate resources. Moreover, the service provider offers cloud services to several users based on pay-as-you-go-basis, where each user will be able to request tasks either individually or as a group. During the request, users also specify the particular resource requirements, expected deadlines, and other essential details that are necessary for successful task execution [21]. The payments to the service provider are based on the duration of resources, which are allocated to execute jobs, while a broker continuously monitors the status of these tasks. Once the tasks are requested, the service provider utilizes a task scheduler for organizing and assigning the tasks to the most suitable resources at specific times.

3.2.1. Average Sample Learning Strategy Based on Horse Herd Optimization

The presented HHO algorithm is one of the swarm intelligence-based algorithms that reflects the horse herd's social behavior and movement patterns. Especially, the HHO algorithm focuses on the herd's dynamic leadership as well as the collective intelligence during migration to prevent predators during a search for food resources. This leadership and collective intelligence help allocate the resources efficiently for scheduled tasks in the CC environment.

The proposed HHO algorithm involves six behavior patterns of horses in their environment and social performance at distinct ages of life. Horse behaviors include Grazing(G), Sociability (S), Hierarchy (H), Defense Mechanism (D), Imitation (I), and Circulation/Roaming (R). A mathematical representation of the movement of horses in every phase is given in the Equation (1):

$$y_p^{Iter,a} = v_p^{\rightarrow Iter,a} + y_p^{(Iter-1),a}, \qquad a = \alpha, \beta, \gamma, \delta \ (age\ groups) \tag{1}$$

Where, $y_p^{Iter,a}$ and $v_p^{\rightarrow Iter,a}$ represents horse's location p at iteration $Iter$ and Iter − 1; a denotes horse's age; $Iter$ refers to current iteration; $v_p^{\rightarrow Iter,a}$ indicates horse speed. Generally, the horses are divided into four classes according to their age, which is described below:

- δ –ages between 0 - 5 years,
- γ - ages among 5 - 10 years,
- β- ages between 10 - 15 years,
- α - older than 15 years.

Horse's movement between various age groups during every iteration is represented mathematically in Equations (2) to (5):

$$v_p^{\rightarrow Iter,\alpha} = G_p^{\rightarrow Iter,\alpha} + D_p^{\rightarrow Iter,\alpha} \tag{2}$$

$$v_p^{\rightarrow Iter,\beta} = G_p^{\rightarrow Iter,\beta} + S_p^{\rightarrow Iter,\beta} + H_p^{\rightarrow Iter,\beta} + D_p^{\rightarrow Iter,\beta} \tag{3}$$

$$v_p^{\rightarrow Iter,\gamma} = G_p^{\rightarrow Iter,\gamma} + S_p^{\rightarrow Iter,\beta} + H_p^{\rightarrow Iter,\beta} + D_p^{\rightarrow Iter,\beta} + I_p^{\rightarrow Iter,\gamma} + R_p^{\rightarrow Iter,\gamma} \tag{4}$$

$$v_p^{\rightarrow Iter,\delta} = G_p^{\rightarrow Iter,\delta} + I_p^{\rightarrow Iter,\delta} + R_p^{\rightarrow Iter,\delta} \tag{5}$$

The six behaviors of horses in the HHO algorithm are clearly described as follows:

Grazing (G): The horses in the HHO algorithm have the general behavior of grazing, where they spend 16-20 hours per day moving freely and grazing endlessly throughout their life. The grazing behavior in HHO is mathematically represented in Equations (6) and (7):

$$G_p^{\rightarrow Iter,a} = g_{Iter}\begin{pmatrix}\breve{u}+\\ \rho\breve{l}\end{pmatrix}\left[y_p^{(Iter-1),a}\right],\ a=\alpha,\beta,\gamma,\delta \quad (6)$$

$$g_p^{\rightarrow Iter,a} = g_p^{(Iter-1),a}\times\omega_g \quad (7)$$

Where, $G_p^{\rightarrow Iter,a}$ denotes the moving parameter of horses, which decreases for every iteration based on ω_g; $\check{l}$ and $\breve{u}$ values of the low and high limits of the grazing area. In this grazing phase, the algorithm searches the cloud environment for a better configuration to optimize the resources in a cloud environment.

Hierarchy (H): Some of the horses in the herd are horse leaders, and the rest of the herd behaves as followers. The horse leader behaves as a director of the other horses, where both male and female horses are able to lead a horse herd. A horse with strong and knowledgeable horse is considered the leader horse, which is denoted as h. The position of horses in the hierarchy phase is expressed mathematically in the Equations (8) and (9):

$$H_p^{\rightarrow Iter,a} = h_m^{Iter,a}\left[y_*^{(Iter-1)} - y_p^{Iter,a}\right],\ a=\alpha,\beta,\gamma, \quad (8)$$

$$h_p^{Iter,AGE} = h_p^{(Iter-1),AGE}\times\omega_h \quad (9)$$

Where, $H_m^{\rightarrow Iter,a}$ denotes the effect of best horse positions based on speed; $X_*^{(Iter-1)}$ represents the position of the optimal horse. In the hierarchy phase, the algorithm finds the best resource configuration to process transactions efficiently and reduce the transaction delay.

Sociability (S): In the HHO algorithm, the horses that live together, where some of the horses live in groups while making contact or fighting with other animals. This social behavior of horses in the environment is determined by parameters that make a life for their survival and welfare in their inclination to update other horse positions. The updated positions of horses in the HHO algorithm based on social behavior are given in Equations (10) and (11):

$$S_p^{\rightarrow Iter,a} = s_p^{Iter,a}\left[\left(\frac{1}{N}\sum_{f=1}^{N} y_p^{(Iter-1)}\right) - y_p^{(Iter-1)}\right],\ a=\beta,\gamma, \quad (10)$$

$$s_p^{Iter,a} = s_p^{(Iter-1),a}\times\omega_s \quad (11)$$

Where, $s_p^{Iter,a}$ indicates movement direction. N denotes the total number of horses. In this phase, all parts of the cloud infrastructure are utilized together to handle transactions seamlessly in small finance.

Imitation (I): This imitation behavior of horses in the HHO algorithm represents that they reflect each other's actions, like finding the right location for grazing from the adult horses. Here, the degree of imitation behavior between horses is evaluated by a variable, which is represented as i. The mathematical representation of the imitation behavior of horses is formulated in Equations (12) and (13):

$$I_p^{\rightarrow Iter,a} = i_p^{Iter,a}\left[\left(\frac{1}{\rho N}\sum_{f=1}^{\rho N}\hat{y}_p^{(Iter-1)}\right) - y_p^{(Iter-1)}\right],\ a=\gamma \quad (12)$$

$$i_p^{Iter,\ a} = i_p^{(Iter-1),a}\times\omega_i \quad (13)$$

Where, $I_p^{\rightarrow Iter,a}$ denotes horse movement according to its position $\hat{y}$; ρN indicates the percentage of horses that attained high positions. By imitating the best resource allocation technique, the transaction system adapts quickly and handles similar transaction processes efficiently.

Defense Mechanism (D): In this phase, horses represent protective actions, which are categorized into two types: fleeing from attack or living in harmony with the aggressor. This defense mechanism in the proposed HHO algorithm is expressed in Equations (14) and (15):

$$D_p^{\rightarrow Iter,\ a} = -d_p^{Iter,a}\left[\left(\frac{1}{qN}\sum_{f=1}^{qN}\hat{y}_p^{(Iter-1)}\right) - y_p^{(Iter-1)}\right],\ a=\alpha,\beta,\gamma \quad (14)$$

$$d_p^{Iter,a} = d_p^{(Iter-1),a}\times\omega_d \quad (15)$$

Where, $D_p^{\rightarrow Iter,\ a}$ refers to a vector of horse escape; ω_d indicates reduction rate per iteration; d indicates protective actions of horses; qN represents the count of horses with the least favorable locations. This defense mechanism protects the transaction from attacks and overloads that ensure secure transactions in small finance.

Roaming (R): Naturally, the horses explore new places out of curiosity, change their location between grasslands, and search nearby pastures. These erratic movements of horses in the herd are represented by a coefficient r, which represents more common behavior between young horses and leads to weakness as they grow older. This roaming behavior of horses in the HHO algorithm is mathematically represented in Equations (16) and (17):

$$R_p^{\rightarrow Iter,a} = -r_p^{Iter,a}\rho y_p^{(Iter-1)},\ a=\gamma,\delta \quad (16)$$

$$r_p^{Iter,a} = r_p^{(Iter-1),a}\times\omega_r \quad (17)$$

Where, $R_m^{\rightarrow Iter,a}$ represents the horse speed vector during the random escape from local minima; ω_r denotes a decrease in a constant per iteration. Based on the transaction volumes, the transaction system searches for new resource configurations to confirm that the system remains optimized.

ASL Strategy

In the proposed HHO algorithm, the updated position of horses in the hierarchical phase selects the best horse for the most suitable position in the search space. This random update in horse position leads the algorithm to fall into a local optimum and provide suboptimal results that affect the efficient resource allocation in CC. Therefore, an ASL strategy is integrated during the position update phase of the horses and improves the exploration ability of the HHO algorithm. To identify and estimate the new position of horses in the hierarchy phase is represented in Equations (18) to (20):

$$H_p^{\rightarrow Iter,a} = \left(h_p^{Iter,a}(t+1) = h_p^{Iter,a}(t) + r.(y_*^{Iter,a} - Tm.\, y_p^{Iter,a}(t)\right) \quad (18)$$

$$y_p^{Iter,a}(t+1) = \frac{y_p^1 + y_p^2 + y_p^3}{3} \quad (19)$$

$$ROBL = \begin{cases} x_j^1 = y_p^{best}(t) - (2.\eta.r - \eta).M_{best} \\ x_j^2 = y_P^{Iter,a}(t) - (2.\eta.r - \eta).M_A \\ x_j^3 = y_p^{Iter,a}(t) - (2.\eta.r - \eta).M_B \end{cases} \quad (20)$$

Where, $h_p^{Iter,a}(t)$ denotes horse position at iteration t; $H_p^{Iter,a}(t)$ represents new position after ASL strategy; r refers to random number; Tm stands for control parameter; $y_p^{Iter,a}(t)$ indicates current position; $h_p^{Iter,a}(t+1)$ updated position of the same agent at iteration $(t+1)$. $y_p^{Iter,a}(t+1)$ denotes average updated position; $y_p^1 + y_p^2 + y_p^3$ indicates the top three candidate positions; $y_p^{best}(t)$ represents best position; η indicates control coefficient; M_{best} and $M_{A,}M_B$ refers to the difference vector obtained from the best solution and agents.

In the HHO algorithm, horse positions are updated based on the best individual in the herd, which often causes the algorithm to become trapped in local optima. Thus, updating the positions of the horses in the herd by using the proposed ASL strategy, which not only depends on the optimal position of the horse in phases of the HHO algorithm but also enhances the resource allocation in the cloud for the scheduled tasks efficiently.

3.2.2. Seamless Transaction in Small Finance

A seamless transaction in small finance refers to a financial transaction that occurs smoothly without any disruptions or delays, ensuring that all involved processes from initiation to completion are efficient and error-free. In the context of small finance organizations, resource allocation is important because these finance institutions in the cloud often have limited resources, and they also need to maintain high standards of service to retain customer trust and satisfaction. In small finance, providing seamless transactions is crucial for customer satisfaction and retention. Offering a smooth and reliable transaction process can help small finance organizations stand out in a competitive market.

By optimizing the transaction process, small financial institutions can reduce costs and improve overall operational efficiency. The ASL strategy combined with HHO provides a robust approach to secure and dynamic resource allocation in cloud environments, particularly for small finance institutions. By continuously learning from the environment and optimizing resource allocation based on priority, the strategy ensures that transactions are processed seamlessly and securely, even under varying loads and potential security threats. The proposed ASL-HHO approach is essential for maintaining high service levels and customer trust in financial operations.

4. Results and Discussion

Experimental results of the ASL-HHO algorithm based on secure resource allocation in the application of small finance transactions in a CC environment are depicted in this section. In this research, the ASL-HHO method is simulated using Cloud SimTool with a system configuration of an i7 processor, 16 GB RAM, and Windows 10 OS. The quantitative and qualitative analysis of the proposed ASL-HHO algorithm is illustrated in Section 4.1. A comparative study of the based resource allocation model with existing methods is presented in Section 4.2. Performance measures used for evaluation are energy consumption, makespan, and resource utilization.

4.1. Performance Analysis

Performance evaluation of the ASL-HHO algorithm, which is used for secure resource allocation for small finance transactions in the cloud, is presented in Tables 1, 2, and Figures 2 and 3. Quantitative analysis of ASL-HHO based on energy consumption in terms of the number of tasks is presented in Figure 1.

The performance evaluation of the proposed resource allocation model based on energy consumption. State-of-the-art algorithms such as Ant Colony Optimization (ACO), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and conventional HHO algorithms, respectively. Figure 2 represents the performance evaluation of the proposed resource allocation model based on makespan. The proposed ASL-HHO algorithm is analyzed with various traditional methods, namely PSO, GA, ACO, and conventional HHO algorithms, respectively.

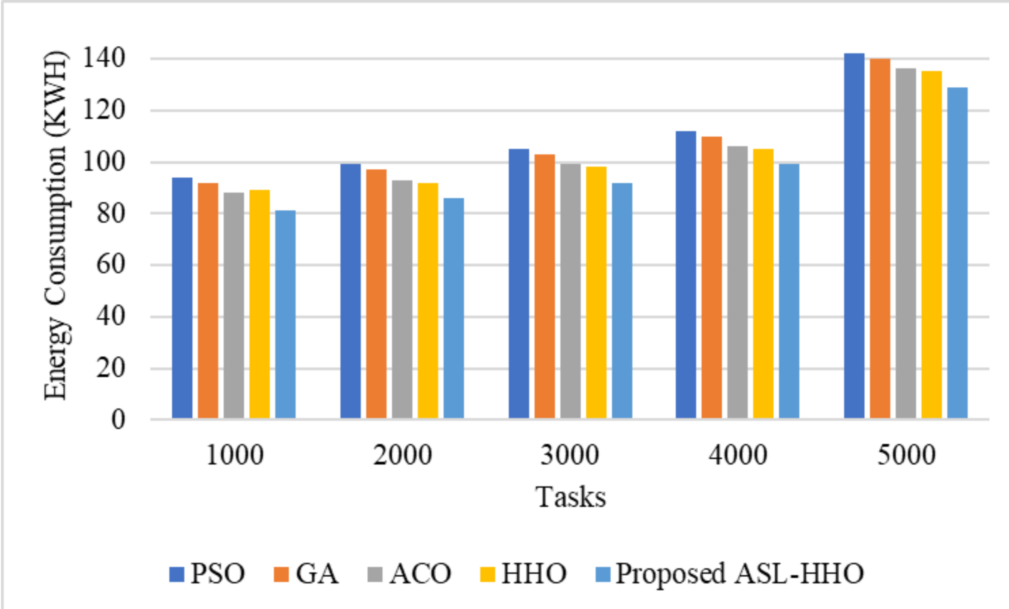

Fig. 2 Evaluation of proposed ASL-HHO in terms of energy consumption (KWH)

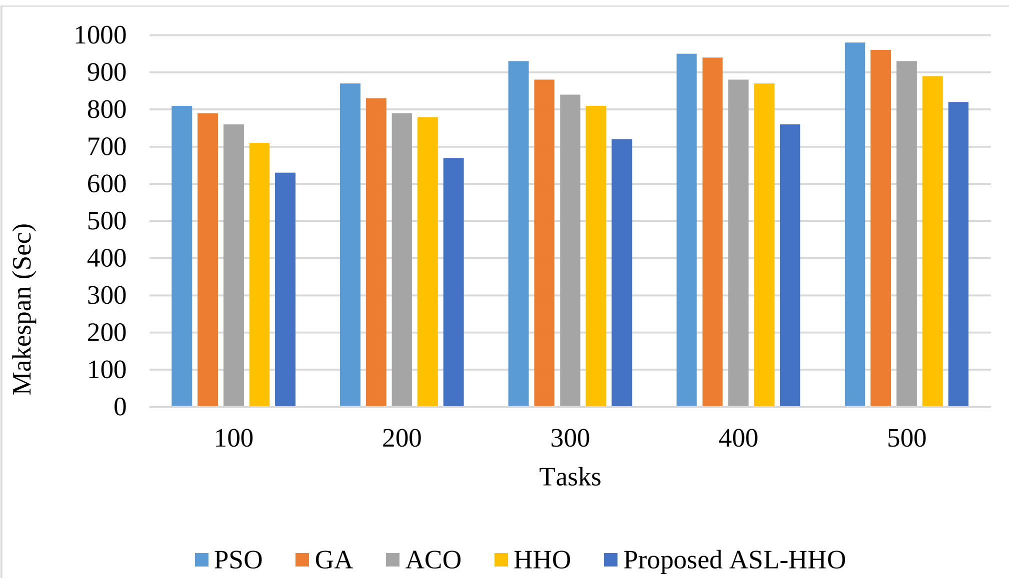

Fig. 3 Comparative evaluation of the proposed ASL-HHO algorithm with existing metaheuristic algorithms in terms of makespan (sec)

The quantitative results of resource utilization by the proposed ASL-HHO algorithm on various sets of tasks are represented in Table 1. The ASL-HHO algorithm-based resource allocation model in the cloud is analyzed and evaluated with conventional algorithms, namely PSO, GA, ACO, and HHO, respectively.

Table 2 represents computational complexity and statistical analysis of ASL-HHO-based secure resource allocation in the cloud. From the results, it is observed that the proposed resource allocation model achieved superior performance in secure resource allocation by effectively balancing exploration and exploitation phases through an integrated learning strategy. Its efficient task–resource mapping reduces the computational time and memory consumption, which ensures the optimal use of cloud resources for the scheduled user tasks.

The integration of security-aware parameters, such as quality of service constraints that lower the p-value, is evaluated based on the resource utilization parameter, which indicates that the proposed model is statistically significant compared to the existing traditional algorithm. Moreover, fast convergence of the ASL-HHO algorithm accelerates inference time, which allows the model to allocate the most appropriate resources to the tasks.

Table 1. Evaluation of ASL-HHO in secure resource allocation based on resource utilization

Methods	Tasks				
	100	200	300	400	500
PSO	1799	2136	2495	26 788	33 225
GA	1873	2391	2627	29 563	36 469
ACO	1964	2769	3258	32 874	38 597
HHO	2245	2987	3649	33 154	41 252
Proposed ASL-HHO	2896	3589	4215	34 459	42 741

Table 2. Evaluation of computational and statistical performance of the proposed ASL-HHO algorithm for secure resource allocation in a cloud environment

Methods	Computational time (s)	Memory usage (MB)	p-value	Inference time (s)
PSO	5.42	220	0.047	3.25
GA	6.18	245	0.052	3.67
ACO	5.95	230	0.049	3.41
HHO	4.87	210	0.041	2.98
Proposed ASL-HHO	3.12	180	0.028	2.15

4.2. Comparative Analysis

Comparative study of the ASL-HHO model is evaluated with previous resource allocation methods in CC, such as AMO-TLO [16], SMO [17], and CS-HBO [18], which are represented in this section. Tables 3 to 5 illustrate a comparative evaluation of the proposed resource allocation algorithm with existing resource allocation methods in different scenarios.

Table 3. Comparative analysis of proposed ASL-HHO vs AMO-TLO [16]

Methods	Metric	Tasks				
		500	1000	1500	2000	2500
AMO-TLO [16]	Makespan (Sec)	900	1800	2500	3000	4100
Proposed ASL-HHO		825	1570	2200	2600	3300

Table 4. Comparative analysis of proposed ASL-HHO vs SMO [17]

Models	Metrics	Tasks				
		3500	4000	4500	5000	5500
SMO [17]	Makespan (in hours)	2.3	2.8	3.0	3.3	3.5
	Energy Consumption (Kilowatt per hour)	100	115	122	144	163
Proposed ASL-HHO	Makespan (in hours)	1.8	2.3	2.5	2.8	3.0
	Energy Consumption (Kilowatt per hour)	92	99	113	129	146

Table 5. Comparative analysis of proposed ASL-HHO vs CS-HBO [18]

Methods	Metrics	VMs			
		250	300	350	400
CS-HBO [18]	Resource utilization	6393	3668	9312	31 130
	Makespan (ms)	0.76	0.44	1.12	3.74
Proposed ASL -HHO	Resource utilization	6936	4215	9945	34 459
	Makespan (ms)	0.61	0.32	0.97	1.26

4.3. Discussion

The proposed ASL-HHO algorithm is utilized for secure resource allocation in the cloud for seamless transactions in small finance, achieving better results. However, the prior resource allocation models have limitations, such as AMO-TLO [16]; the adaptive nature of the developed optimization model was not sufficient to quickly respond to rapid changes in QoS requirements and emerging security threats. The SMO [17] algorithm has slow convergence that leads to delays in resource allocation decisions. The combination of two metaheuristic optimization algorithms, namely the CS-HBO [18] algorithm, conflicted with each other in certain circumstances, making the resource allocation model difficult to allocate resources, which led to inefficient resource allocation.

To overcome these limitations and enhance secure resource allocation in the cloud, the ASL-HHO algorithm is proposed for optimal resource allocation. Utilizing a sample learning strategy makes the HHO algorithm more resilient to dynamic changes in the cloud environment, such as fluctuating workloads or varying security threats. By averaging multiple potential solutions, the strategy improves the accuracy of decision-making in resource allocation. This leads to a more precise allocation of resources, ensuring security and performance needs are met without unnecessary over-provisioning. By learning from past transactions, the ASL strategy and the defense mechanism in the HHO algorithm help detect fraud or malicious activity earlier, which enables the system to react quickly and protect sensitive financial information. This enhances the security of transactions, building trust with users in small finance.

5. Conclusion

The ASL-HHO is proposed for secure resource allocation in the cloud to make seamless transactions in small finance organizations. The ASL strategy is integrated with the HHO algorithm to avoid resource over-commitment by averaging across multiple resource scenarios and adapting to the dynamic nature of the cloud environment, which maintains a balance between resource optimization and security to enhance seamless transactions. The hierarchy phase and imitation behaviors in the HHO algorithm optimize resource use, preventing wastage and ensuring fast transaction processing. The proposed method considers QoS parameters such as make span, energy consumption, trust, and resource utilization for secure resource allocation. The experimental analysis of the proposed ASL-HHO algorithm-based secure resource allocation model attained resource utilization for tasks 100, 200, and 500 of 2896, 3589, and 42741, respectively, efficiently, when compared to existing resource allocation models such as AMO-TLO, SMO, and CS-HBO. In the future, a hybrid optimization algorithm-based resource allocation with an access control technique will be implemented to enhance secure resource allocation in the cloud.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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