

An Optimal Task Scheduling Strategy in Cloud Computing Environment Utilizing FFA-PSO Algorithms

Mrs. Ursa Sayeed¹, Mr. Arshad Shareef², Dr. T Sunil³

^{1,2}Research Scholar Department of CSE

SSSUTMS, Sehore, Bhopal, Madhya Pradesh, (India)

³Professor & Dean Department of CSE

Malla Reddy College of Engineering Hyderabad, Telangana, (India)

ABSTRACT

With the expanding notoriety of cloud computing products, task scheduling issue has turned into a hot research point in this field. The task scheduling problem of cloud computing system is more intricate than the conventional distributed system. To locate a proper trade-off among resource utilization, energy consumption and Quality of Service (QoS) requirements under the evolving condition, the task scheduling is a testing assignment and furthermore the cloud task scheduling is an NP-hard problem. In this paper, to locate the best and the optimal arrangement keeping in mind the end goal to decrease the aggregate processing time for the cloud task scheduling problem, we propose an Adaptive Multi-Objective Task Scheduling (AMTS) strategy. Our proposed algorithm depends on the half and half optimization approach, which combines the Firefly algorithm (FFA) and PSO (Particle Swarm Optimization) algorithms to locate an optimal solution. The principle objective of these algorithms is to decrease the general task processing time, computational cost and the energy consumption of the system. The experimental result demonstrates that the half breed FFA-PSO perform superior to the next optimization algorithms for the cloud task scheduling problem.

Keywords: Adaptive Multi-Objective Task Scheduling(AMTS), Cloud Computing, Fire Fly Algorithm (FFA), PSO (Particle Swarm Optimization), Task Scheduling .

1.INTRODUCTION

Cloud computing is another computing model [1]. It includes an expansive number of PCs associated through a correspondence network, for example, the internet, like utility processing [2]. The cloud computing is normally in ultra large scale and high scalability. To be more particular, cloud computing can be connected with countless resources and constitute a substantial scale asset pool [3]. And after that this size can be dynamically balanced by the application and request, which can make full utilization of the different resources in the cloud computing framework to give administrations to clients and applications [3]. At the end of the day, cloud computing can at the same time process various occupations from various clients by giving dynamically scalable and virtualized



resources as a service [4]. It implies that cloud computing can get higher execution by optimizing the portion of resources to tasks [5].

The task scheduling issue is a troublesome issue in the research field of cloud computing [6]. As indicated by the attributes of cloud computing, the task ought to be appointed to various resource nodes relating to performing proper systems, with a specific end goal to accomplish a superior outcome [7]. It comprises of dispensing reasonable resources to the assignments in order to limit or amplify a specific objective function that can be either makespan, execution time, resource utilization or throughput [8]. Task scheduling is a standout amongst the most basic issues on cloud platforms. The quantity of clients is enormous and data volume is huge. Solicitations for resource sharing and reuse turn out to be increasingly basic [9]. An Efficient task scheduling component should meet clients' prerequisites and enhance the resource usage, in order to upgrade the general execution of the cloud computing environment.

Cloud task scheduling can be depicted as an NP-hard optimization issue [10], and these task scheduling issue can be settled by utilizing Meta-Heuristic Algorithms, for example, Genetic Algorithm (GA), Ant Colony Optimization (ACO), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Max-Min Algorithm and numerous more to unravel this task scheduling issue. In task scheduling, the ACO [11] is used for limiting the aggregate processing time. Notwithstanding, amid the season of refreshing the pheromone intensity, the ACO algorithm has a few issues. To optimize the makespan, the Genetic Algorithm [12] is used, yet this strategy has two primary drawbacks, they are many-sided quality and longtime utilization. Considering both the cost of data transmission and computation, a PSO algorithm [13] has been actualized to schedule the tasks. By and by, the total of transmission time and the task processing time is high.

In this paper, we propose an Adaptive Multi-Objective Task Scheduling (AMTS) system to acquire the best and the optimal arrangement of the task to diminish the task completion time for the cloud task scheduling issue. The proposed technique is the blend of the FFA and PSO algorithm to acquire the optimal arrangement. The primary objective of this exploration is to limit the task processing time, computational cost and expanding the resource utilization.

The rest of the segment of the work is delineated in the area underneath. Area 2 clarified the literature review, the proposed FFA-PSO based AMTS approach is portrayed in segment 3, the results and the conclusion are delineated in segment 4 and 5.

II. RELATED WORKS

J. Yang et al. [14] have proposed a game theory approach for energy administration in cloud computing task scheduling algorithm. The creator has additionally presented a balanced scheduling algorithm in light of the task scheduling algorithm and it considers the unwavering quality of the task. The computing nodes of the task scheduling model are proposed in light of the balanced scheduling algorithm. In their approach, rate allocation system on the node is figured by using the game theory approach.

For the optimal task scheduling in cloud environment, H. He et al. [15] have built up a PSO-based Adaptive Multi-Objective Task Scheduling (AMTS) Strategy for lessening the processing time and transmission time. At that point the creator has been executed a task scheduling policy to get the optimal resource use, task completion time, average cost and the average energy consumption. They additionally adjusted an adaptive acceleration coefficient to keep up the particle diversity. In their approach, the quasi-optimal solutions are gotten by using the enhanced PSO algorithm.

For the task scheduling in cloud computing Bei Wang et al. [16] have displayed a cost-effective precedence constrained task scheduling algorithm. The algorithm considers the financial COST and tries to satisfy a task scheduling balancing time and cost. So as to investigate more conceivable arrangements with top notch overlooked by the deterministic algorithm, multi-population genetic algorithm was embraced to gain the normal schedule plot. In addition, keeping in mind the end goal to enhance the execution on time expending of the algorithm, enhanced task duplication with financial cost limitation was actualized. Contrasted and deterministic scheduling algorithm, their algorithm decreases the cost incredibly. In the mean time, its execution on time devouring can likewise be ensured to some degree.

W. Chen et al. [17] have proposed an effective algorithm of minimizing the schedule length using the budget level (MSLBL) to choose processors for fulfilling the budget constraint and limiting the schedule length of an application. Such issues was decayed into two sub-problems, to be specific, fulfilling the budget constraint and limiting the schedule length. The main sub-issue was understood by exchanging the budget constraint of the application to that of each TASK, and the second sub-issue was fathomed by heuristically scheduling each TASK with low-time complexity. Trial comes about on a few genuine parallel applications approve that their MSLBL algorithm can acquire shorter schedule lengths while fulfilling the budget constraint of an application than existing strategies in different circumstances.

A three meta-heuristic strategies, for example, simulated annealing, firefly algorithm and cuckoo search algorithm have been executed by T. Mandal and S. Acharyya [18] to locate an optimal answer for taking care of the task scheduling issue in a cloud computing environment. The principle objective of their algorithms was to limit the general processing time of the VMs which execute an arrangement of TASKS. Their trial result demonstrates that the firefly algorithm (FFA) performs superior to anything simulated annealing and cuckoo search algorithm.

A multi-objective task scheduling issue with required buyers' QoS desires and a scheduling model in connection to the issue is introduced D. Gabi et al. [19]. A dynamic multiobjective orthogonal taguchi based-cat (dMOOTC) algorithm was then actualized to settle the model. cloudsim tool was utilized for the use of the their algorithm and assessed with measurements of execution time, execution cost, and QoS. In their approach, the execution result as contrasted and standard cat swarm optimization (CSO), multi-objective particle swarm optimization (MOPSO), enhanced parallel CSO (EPCSO), orthogonal taguchi based-cat algorithm (OTB-CSO) demonstrates the arrangement beat better by returning great customers' QoS desired.

K. Kaur et al. [20] have exhibited a context and load aware strategy for proficient task scheduling utilizing a changed genetic algorithm known as family genetic algorithm. In light of investigation of client attributes, client demands are satisfied by the correct kind of resource. Such a classification accomplishes productive scheduling and enhanced load balancing and will demonstrate favorable for the eventual fate of the cloud. Results demonstrate that the proposed method was productive under different conditions.

III. PROPOSED APPROACH PRELIMINARIES

3.1 AMTS System Model and Problem Formulation

The cloud computing is basically utilized in fulfilling the various tasks and quality of service (QoS) prerequisites of the clients. The cloud computing environments furthermore fuse the resources of the income suppliers and the energy preservation. The principle objective of this research procedure is to learn, the better QoS, resource effectiveness and energy protection. In the cloud computing environments, the cloud resources solidifies different autonomous tasks and theories free tasks consolidates various subtasks. To find out the optimal resource in light of the client necessity the task scheduling approach is used.

3.2. Mathematical Model

There are five sorts of situations are considered in the cloud task scheduling process. At first, each task in the cloud renders a number of a various variety of subtasks. In the second situation, the information can be transmitted between the subtasks. In the third situation, an assortment of processing capacities is taken care of by the processors. In the fourth situation, various types of nodes have the diverse bandwidth ratio, this bandwidth is changing after some time. In the fifth situation, the aggregate task completion time is the sum of the task execution time and task communication time.

Let us consider the tasks $X = \{x_1, \dots, x_i, \dots, x_m\}$, here, the number of subtasks of the task X is given viz,

$$N = \sum_{i=1}^m |x_i| \quad (1)$$

In the above equation, the total number of sub tasks is denoted as N , the number of subtasks of the task i is represented as $|x_i|$. In the scheduling process, the physical resource node and the virtual resource nodes are considered as follows,

$$P_r = \{P_1, P_2, \dots, P_n\} \quad (2)$$

$$V_r = \{V_1, V_2, \dots, V_j\} \quad (3)$$

The distribution relationship between the task X and the resource node V is computed by utilizing the following distribution matrix equation,

$$D_m = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m1} & \dots & d_{mn} \end{bmatrix} \quad (4)$$

In the above equation, $\sum_{j=1}^n d_{ij} = |x_i|$. In the all resource nodes, the execution time of the each subtask is computed by using the following set matrix equation,

$$SET = \{SR_i / K_j\} \quad (5)$$

In the above equation, $SET = \{set_{ij}\}$, here, in x_i task, the data block size of the each subtask is represented as SR_i , the processing capacity of V_j is represented as K_j . Here, the ranges of i and j is $i = \{1, 2, \dots, m\}$ and $j = \{1, 2, \dots, n\}$. The communication time amid the time of data exchange between the two distinct nodes in task x_i are computed as follows,

$$C_{t_i} = \sum_{l=1}^{|x_i|-1} \sum_{q=l+1}^{|x_i|} Z_i^{lqab} * (SX_i^{lq} / F_i^{lq}) \quad (6)$$

Where, the communication time is represented as C_{t_i} and the a, b is the two different nodes V_a, V_b . Here,

$$\sum_a \sum_{b=1}^{n-1} Z_i^{lqab} = 1 \text{ and the value of } q \text{ being ranges from 1 to } x_i.$$

The execution time on the virtual node V_j is expressed as follows,

$$E_j = \sum_{i=1}^m d_{ij} * set_{ij} \quad (7)$$

The total task completion time is expressed as follows,

$$Total = \max_{j=1}^n E_j + \max_{i=1}^m C_{t_i} \quad (8)$$

In the all resource nodes, the energy consumption of the each subtask is computed by using the following set matrix equation,

$$E_{cons} = \sum_{i=1}^m \sum_{j=1}^n d_{ij} * g_{ij} \quad (9)$$

In the above equation, $E_{cons} = \{g_{ij}\}$, here, in x_i task, the energy consumption of the each subtask is represented as g_{ij} . At the point when the above computed energy consumption value is high, the resource utilization is low, generally the resource usage is high. The resource utilization is computed as follows,

$$R_{util} = 1 - \sum_{j=1}^n \frac{(Total - E_j)}{(m * Total)} \quad (10)$$

The cost of the all subtasks of task x_i is computed as follows,

$$Cost = \sum_{j=1}^n (E_j * R_{Cj}) + \sum_{i=1}^m C_{t_i} * T_C \quad (11)$$

In the above equation, the resource computation cost is represented as R_{Cj} , the transmitting data time is represented as T_C . The primary target of this research is, diminish the processing time, energy consumption and cost, optimize the resource utilization.

3.3. Combined FFA-PSO Algorithm for AMTS

The proposed algorithm relies upon the creamer optimization approach, which consolidates the firefly algorithm (FFA) and PSO (particle swarm optimization) algorithms to find an optimal solution. The standard goal of these algorithms is to diminish the general task processing time, computational cost and the energy consumption of the framework.

3.3.1. Firefly Algorithm (FFA)

The firefly algorithm enhanced in view of the blazing example and conduct of fireflies and it unites three principle rules, they are: (1) The fireflies are pulling on each other in light of their sex. (2) The fireflies pull in different fireflies in light of the splendor, if there is no brighter one, they will move randomly. (3) The objective function's landscape is used to choose the shine of the firefly. Here, the fitness function is registered for every solution and which solution has the better fitness, it is considered as the brightest firefly and these better fitness (brighter firefly) is updated.

Step (i): Initialization

In the initialization step, the population of the fireflies is randomly initialized. The fundamental task in the introduction is to produce the number of fireflies, which are randomly as indicated by the relating look space. Initialize the population solutions,

$$X = \{x_1^l, x_2^l \dots x_n^l\} \quad (12)$$

In the above equation, in $l - th$, generation the position of the $i - th$ firefly is represented as x_i^l .

Step (ii): Objective Function Creation

The task is scheduled based on the fitness function. Here, the task is scheduled based on the total execution cost and total task completion time,

$$fitness = \begin{cases} \text{minimize} : E_j, C_{t_i} \text{ and } E_{cons} \\ \text{maximize} : R_{uti} \\ \text{subject to} : Total = \max_{j=1}^n E_j + \max_{i=1}^m C_{t_i} \leq T^D \end{cases} \quad (13)$$

Step (iii): Updation

The solutions are updated using the firefly algorithm and the solutions are updated utilizing the following equation,

$$A_i^{k+1} = A_i^k - \gamma_0^{uk} e^{-Ad_j^2} (A_j^k - A_i^k) + \Omega_k \eta_i^k \quad (14)$$

Where, the new update solution is represented as A_i^{k+1} , the present i-th solution is represented as A_i^k and the j -th solution is represented as A_j^k . Here, the arbitrary parameter is represented as Ω_k , at time t the random distribution is represented as η_i^k and the constants are denoted as γ_0^{uk} and A .

3.3.2. Particle Swarm Optimization (PSO) Algorithm

For updating the objective function of FFA, the PSO algorithm is utilized in this part. For improving the performance of the FF algorithm PSO is updated. Here, the energy consumption, total task completion time is minimized and the resource utilization is maximized. The above criteria should be satisfied and the optimal results with the help of PSO algorithm are achieved in the paper.

Step (iv): PSO for updating

The position and velocity of the solution are computed based on the following equation,

$$A_i^{k+1} = A_i^k + S_i^{k+1} \quad (15)$$

$$S_i^{k+1} = S_i^k + (S_j^k - S_i^c) * H_i \quad (16)$$

$$H_i = H_{\min} + (H_{\max} - H_{\min}) * \gamma \quad (17)$$

In the above equation, the new update solution is represented as A_i^{k+1} , the i-th solution is represented as A_i^k and the j -th solution is represented as A_j^k .

Step (v): Termination

Save the best solution achieved so far and minimize the energy consumption and total task completion time of the real and reactive task variations. Then save the corresponding parameters, check the iteration range, if the iteration has not achieved the maximum range, increase the iteration count as $k = k + 1$, or else terminate the process.

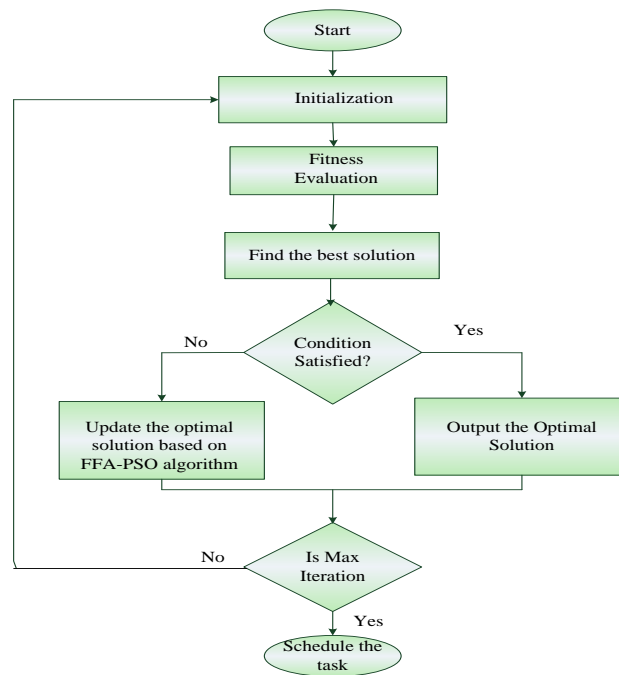


Figure.1: Flowchart of FFA-PSO Algorithm

IV.RESULTS AND DISCUSSIONS

In this section, the combined FFA-PSO algorithm is utilized for the performance evaluation. The proposed algorithm is utilized for minimization of the energy consumption and total task completion and maximizing the resource utilization. Here, the performance of the proposed FFA-PSO algorithm is compared with the existing PSO based AMTS [22] approach. Here, the proposed approach has minimum energy consumption and task completion time and maximum resource utilization.

4.1. Performance Analysis

(a) Task Completion Time

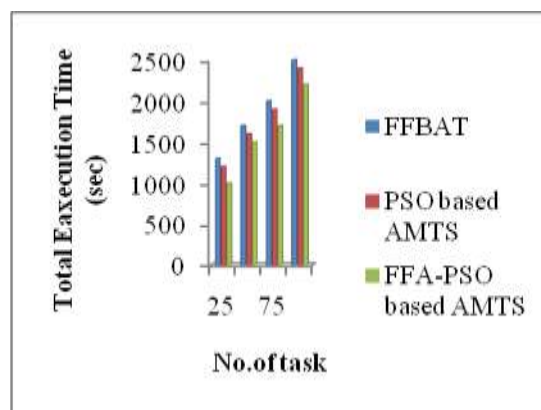


Figure.2: Total Task Completion Time

Figure2 demonstrates the total task completion time of the proposed FFA-PSO technique and it contrasted with the FFBAT (Firefly and Bats algorithm) and PSO based AMTS strategies. The figure shows that the number of tasks is increased, the execution time is also increased. The number of tasks is varied from 25 to 100 and the execution time is plotted with respect to the time and the varying number of tasks. The proposed approach achieves a total execution time is 1600 (s) which is almost equal when compared with the execution time of the (1775 (s)) existing PSO based AMTS approach. The slight increase in execution time is not a matter. The proposed FFA-PSO based AMTS procedure has better execution time when contrasted with the other two methods.

(b) Average Energy Consumption

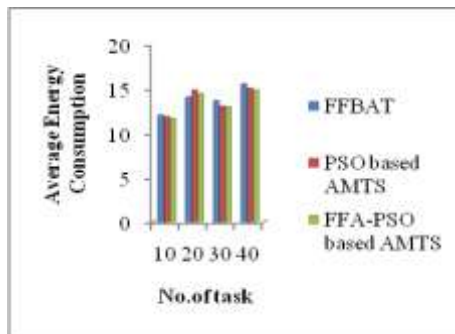


Figure.3: Average Energy Consumption

Energy consumption is the total amount of energy required to transmit the data packet from the one node to the other node. Here, the energy consumption of the proposed work estimated by the measurement of the various task scheduling approaches time slots is compared with the existing techniques. The energy consumption of the proposed FFA-PSO based AMTS method is depicted in the Figure 3. When compared with the existing PSO based AMTS and FFBAT technique, the proposed FFA-PSO technique required less energy to transmit the information. Due to this reason, the quality of the resources of the proposed FFA-PSO technique is enhanced.

(c) Average Cost

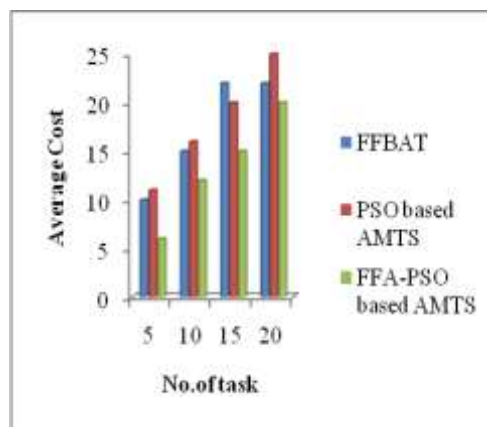


Figure.4: Average Cost

The average cost is the total amount of cost required to transmit the data packet from the one node to the other node. Here, the cost of the proposed work estimated based on the resource utilization of the various task scheduling approaches cost and it is compared with the existing techniques. The average cost of the proposed FFA-PSO based AMTS method is depicted in the Figure 4. When compared with the existing PSO based AMTS and FFBAT technique, the proposed FFA-PSO technique required less cost to transmit the information. Due to this reason, the quality of the resources of the proposed FFA-PSO technique is enhanced.

V. CONCLUSION

This paper proposes a hybrid FFA-PSO based AMTS method for minimizing the total energy consumption, total cost, execution time and maximizing resource utilization. The proposed task scheduling approaches utilizing an FFA and PSO algorithm and which assesses the optimum resources from the every accessible task. The proposed protocol is contrasted with the current PSO based AMTS approach and the FFBAT algorithm to assess the execution of the cloud. The trial result demonstrated that the proposed FFA-PSO based AMTS approach worked proficiently to upgrade the QoS of the resources of task scheduling process in a cloud computing environment in view of the minimum execution time, energy consumption, cost.

REFERENCES

- [1]D. Gabi, A. Ismail, A. Zainal and Z. Zakaria, "Solving Task Scheduling Problem in Cloud Computing Environment Using Orthogonal Taguchi-Cat Algorithm", *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 7, no. 3, p. 1489, 2017.
- [2]A. Arunarani, D. Manjula and V. Sugumaran, "FFBAT: A Security and Cost-Aware Workflow Scheduling Approach Combining Firefly and Bat Algorithms", *Concurrency and Computation: Practice and Experience*, vol. 29, no. 24, p. e4295, 2017.
- [3]J. Chen, "Research on Resource Scheduling in Cloud Computing Based on Firefly Genetic Algorithm", 2017.
- [4]T. Wang, Z. Liu, Y. Chen, Y. Xu and X. Dai, "Load Balancing Task Scheduling Based on Genetic Algorithm in Cloud Computing", 2014 IEEE 12th International Conference on Dependable, Autonomic and Secure Computing, 2014.
- [5]T. Wang, X. Wei, C. Tang and J. Fan, "Efficient multi-tasks scheduling algorithm in mobile cloud computing with time constraints", *Peer-to-Peer Networking and Applications*, 2017.
- [6]Y. Xiong, S. Huang, M. Wu, J. She and K. Jiang, "A Johnson's-Rule-Based Genetic Algorithm for Two-Stage-Task Scheduling Problem in Data-Centers of Cloud Computing", *IEEE Transactions on Cloud Computing*, pp. 1-1, 2017.
- [7]D. Ergu, G. Kou, Y. Peng, Y. Shi and Y. Shi, "The analytic hierarchy process: task scheduling and resource allocation in cloud computing environment", *The Journal of Supercomputing*, vol. 64, no. 3, pp. 835-848, 2011.
- [8]M. Abdullahi, M. Ngadi and S. Abdulhamid, "Symbiotic Organism Search optimization based task scheduling in cloud computing environment", *Future Generation Computer Systems*, vol. 56, pp. 640-650, 2016.

- [9]X. Wu, M. Deng, R. Zhang, B. Zeng and S. Zhou, "A Task Scheduling Algorithm based on QoS-Driven in Cloud Computing", *Procedia Computer Science*, vol. 17, pp. 1162-1169, 2013.
- [10]J. Tsai, J. Fang and J. Chou, "Optimized task scheduling and resource allocation on cloud computing environment using improved differential evolution algorithm", *Computers & Operations Research*, vol. 40, no. 12, pp. 3045-3055, 2013.
- [11]F. WANG, M. LI and W. DAUN, "Cloud computing task scheduling based on dynamically adaptive ant colony algorithm", *Journal of Computer Applications*, vol. 33, no. 11, pp. 3160-3162, 2013.
- [12]C. Liu, C. Zou and P. Wu, "A Task Scheduling Algorithm Based on Genetic Algorithm and Ant Colony Optimization in Cloud Computing", 2014 13th International Symposium on Distributed Computing and Applications to Business, Engineering and Science, 2014.
- [13]S. Sarathambekai and K. Umamaheswari, "Task scheduling using multi-objective hamming discrete particle swarm optimisation in distributed systems", *International Journal of Swarm Intelligence*, vol. 2, no. 234, p. 100, 2016.
- [14]J. Yang, B. Jiang, Z. Lv and K. Choo, "A task scheduling algorithm considering game theory designed for energy management in cloud computing", *Future Generation Computer Systems*, 2017.
- [15]H. He, G. Xu, S. Pang and Z. Zhao, "AMTS: Adaptive multi-objective task scheduling strategy in cloud computing", *China Communications*, vol. 13, no. 4, pp. 162-171, 2016.
- [16]Bei Wang, Jun Li and Chao Wang, "Cost-effective scheduling precedence constrained tasks in cloud computing", 2017 IEEE 2nd International Conference on Cloud Computing and Big Data Analysis (ICCCBDA), 2017.
- [17]W. Chen, G. Xie, R. Li, Y. Bai, C. Fan and K. Li, "Efficient task scheduling for budget constrained parallel applications on heterogeneous cloud computing systems", *Future Generation Computer Systems*, vol. 74, pp. 1-11, 2017.
- [18]T. Mandal and S. Acharyya, "Optimal task scheduling in cloud computing environment: Meta heuristic approaches", 2015 2nd International Conference on Electrical Information and Communication Technologies (EICT), 2015.
- [19]D. Gabi, A. Ismail, A. Zainal and Z. Zakaria, "Quality of Service (QoS) Task Scheduling Algorithm with Taguchi Orthogonal Approach for Cloud Computing Environment", *Recent Trends in Information and Communication Technology*, pp. 641-649, 2017.
- [20]K. Kaur, N. Kaur and K. Kaur, "A Novel Context and Load-Aware Family Genetic Algorithm Based Task Scheduling in Cloud Computing", *Advances in Intelligent Systems and Computing*, pp. 521-531, 2017.